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The Dynamic Effect of Operational Risk and Banking Stability

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ABSTRACT

Banks learn the core operational vulnerabilities of their businesses, and detect the risk indicators according to the operation vulnerabilities. In the last decade, operational risk was the main reason for firms collapse. Operational risk inside the credit, market, and liquidity risk can affect the banking stability, which has not been studied much so far. This paper aims to investigate the research gaps in operational risk based on the guidelines of Bank for International Settlements (BIS) for operational risk. We study the relationship between banking stability and operational risk by using a comprehensive analysis of the effect of operational risk and size on banking stability. This research uses data from Iranian banking system over the period 2006–2015. The results show that operational risk have a significantly negative relationship with banking stability, and this is more intensified when we consider the size and complexity of the bank.

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1. Introduction

Modern financial sectors are a supermarket for financial services that face with different types of risks. For many years, financial institutions believed that credit risk and market risk were the only two types of risks that they could deal with, but during the 1990s, due to the collapse of several financial institutions, this study focuses on operational risk (OR) that caused some financial crises (Xu et al., 2017). In other words, inside the credit and market risks, OR has been recognized as another main source of failures in financial institutions (Li and Evans, 2017; Trung et al., 2018).

The Basel Committee on Banking Supervision (BCBS) (2006) defines OR as a risk that has increased due to inadequate or failed internal processes, people and systems or from external events. Moosa (2007) defined OR as the risk of losses which could create a critical and shocking situation, and increase instability in the bank. OR is as likely knees for firms that if it faces with a crisis, it leads to market collapse (Blunden, 2003). Nowadays, a dramatic increasing in the quantity of OR and its upsetting consequences can cause a range of large monetary losses and devastate reputations by bankruptcy (Chernobai et al., 2011). The financial industry and regulatory authorities also have recognized OR as a major separate risk posing a serious threat to global financial institutions' stability (BCBS2001a; BCBS, 2001b; Curry 2012). This situation provides an opportunity to assess an untested claim that whether OR increases instability in banking or not.

Accordingly, we use data from the Iranian banks to investigate the following questions: What is the relationship between OR and banking stability? And does the OR increase instability in banks? In order to answer these questions, we use the regression model according to calculation of OR based on advanced measurement approach (AMA) and business indicator (BI) (guidelines of "standardized measurement approach for OR" (BCBS, 2016) and "Basel III: Finalizing post-crisis reforms" (BCBS, 2017)). We use also the dynamic panel data to study the relationship between OR and Z-score because Z-score is a universal measure of banking stability (Boyd and Nicolo, 2005; 2006; Leaven and Levine, 2009; Berger et al., 2017). Our results show that a negative significant relationship between OR and Z-score in the Iranian banking system. In other words, this study revealed that OR could lead to collapse and instability in Iranian banks, also size can affect the OR intensification and the banking instability. By and large, the complexity and breadth of the bank have the potential to increase the OR, both affecting the banking instability.

One of the notable features of this research is paying attention to OR and its effect on banking instability, which was not usually considered in Iranian banks. In other words, control and management of operating costs was not an important issue for banks before the increasing effect of the dollar on the Iranian economy and its effects on the bank spread rate, because the main income sources of banks supply from the spread rate and not need to cost control in banks, but precisely in recent years, given the prevailing economic crises, controlling operating costs and securing income from other operating sources in banks has become a significant issue. The innovation of this paper is to address this issue and examine the effect of OR of Iranian banks on the instability of these banks, which is significant in terms of policy from both the banking supervisor and the bank manager.

The remainder of this paper is organized as follows. Section 2 describes the theoretical background on OR and econometric model. In Section 3, details on data gathering is provided, and the methodological model is explained. Section 4 presents our empirical results and finally, Section 5 concludes the paper.

2. Literature Review

A wide variety of events including computer hacking, damaged asset, flawed financial models and products, fraud, theft, poor business practices, loss of key staff members, loss of information, vandalism, natural disasters, and other events lead us to face with OR in financial institutions. Financial institutions began to identify OR from 1990s, after a series of high profile events and corporate failures such as Barings, Allied Irish, Daiwa, etc. (Janakiraman, 2008). Nowadays, financial institutions and banks have been seeking for a complete framework to manage ORs (Chernobai et al., 2006), because OR is classified as a pure risk or an opportunity for a loss that leads banks to a financial loss and finally to banking instability (Micocci et al., 2009; Rajendran, 2012; Ferreira and Dickason-Koekemoer, 2019). Therefore, operational loss is measured before and during the crisis to find whether these events have made the changes (Esterhuysen et al., 2010; Hess, 2011). Anyway, bank managers need to be vigilant about any changes**.**

Ong (2002) argued that OR was a concept for all kinds of possible risks in institutions that could be referred to as "garbage dump". If the bank fail to control and manage the OR effectively, it will lead to demise for the bank (Ferreira, 2015; Sweeting, 2011). Banks encounter the OR events on a daily basis (almost 9–13% of the total risk pie), and according to the latest Basel II/III disclosures, regulatory capital requirements for OR currently account for 10–30% of the total risk of exposure of banks that is predicted to increase further in the future (Ames et al., 2015). One of the important reasons for paying attention to OR in recent years is that OR events may cause other banking risks such as credit risk, liquidity risk, and market risk, all of which can create extremely banking instability (Sturm, 2013).

Dorogovs et al. (2013) defined the banking stability as the ability of bank to function in a sustainable equilibrium and maintain its operations. However, due to the increased performed financial operations, banks became very vulnerable to ORs that can disrupt the banks stability. In 1998, BCBS investigated thirty major OR of banks' manager from different member countries. Results show that all banks under study had some framework for managing OR. After the recent financial crisis, BCBS focused on the OR guideline, and revised it in response to the 2007/2008 crisis. In June 2011, the BCBS published principles for the sound management of OR not only to address the weakness it revealed during the crisis, but also to reflect the knowledge gained with an implementation of the OR framework since 2004 **.**

Nowadays, the documents issued by various regulatory bodies assist as a literature source for OR (BCBS, 2006; 2011; 2016; 2017), because there are business complexities in the bank that highlight modeling OR (Peccia, 2003). In recent decades, the literature of OR in the financial institutions focuses on general managerial and statistical perspectives. In addition, some papers address the financial aspects of OR. General managerial perspective insists on OR modeling, measurements, managerial aspects, and regulations (for example, Dorogovs et al., 2013; Xu et al., 2017). Statistical perspective (with research such as Chernobai et al., 2008 and 2011; Bocker and Kluppelberg, 2010; Eckert and Gatzert, 2017) insists on measuring OR and presents an overview of mathematical and statistical techniques **.**

The existent literature also points to strong links between OR and banks' internal attributes (for example, Chernobai et al., 2011; Wang and Hsu, 2013; Basak and Buffa, 2016; Abdymonumov and Mihov, 2019). In recent years, various studies have modeled OR by using the BCBS model (for example, Peters et al., 2016; Mignola et al., 2016; Voneki, 2018; Hassanein et al., 2019). Yet, few studies have measured OR, and studied its effect on banking stability**.**

OR modeling needs to provide a tool to better manage and minimize the OR in firms by identification, measurement and reporting the level of OR. The importance of operating risk modeling is so that Giraud (2005) showed that the collapse of the long-term capital management in large part was in order to bias model in the risk management process. Giraud also argued that even if OR modeling was not reliable, it might force banks to carry more capital, and its continuity can cause banking instability.

3. Methodological Framework

Modeling of OR based on banking regulations that were issued by BCBS includes a variety of statistical and econometric models to calculate the OR, but generally in recent studies, models are classified into top-down models and bottom-up models, both of which rely on historical data (Janakiraman, 2008). The top-down approach includes basic indicator approach (BIA) and the standardized approach (SA), and the bottom-up approach includes advanced measurement approach (AMA). In other words, regulation based on Basel II defines three basic methods for calculating the OR capital requirement that includes BIA, SA, and AMA. Recently, BCBS provided a consultative document to remove the AMA from the regulatory framework, because it believes that the AMA is inherently complex and lacks comparability (BCBS, 2016). The new approach for calculating OR is a combination of AMA and BI that is called the standardized measurement approach (SMA) for computing OR regulatory capital (BCBS, 2017). The SMA combines the BI and operational loss data in banking systems. BI is a simple financial statement proxy of OR exposure that substitutes the variable gross income used in the simple BIA and SA approaches. The BI uses the profit and loss statement and balance sheet for calculation which has made calculations easier. Equation1 shows how to calculate BI (BCBS, 2017).

$$BI = ILDC + SC + FC \tag{1}$$

[1] *Where:*

Avg = average of the items at the years: t,t-1 and t-2

$$ILCD_{Avg} = min\left[abs\left(II_{Avg} - IE_{Avg}\right); 2.25 * IEA_{Avg}\right] + ABS\left(LI_{Avg} - LE_{Avg}\right) + DI_{Avg}$$

$$SC_{Avg} = max\left\{abs\left(OOI_{Avg}; OOE_{Avg}\right)\right\} + max\left\{abs\left(FI_{Avg} - FE_{Avg}\right)\right\}$$

$$FC_{aVG} = abs\left(net\ P\&L\ TB_{Avg}\right) + abs\left(net\ P\&LBB_{Avg}\right)$$

That Abs is absolute value of the items within the bracket. II and IE are Interest Income and expenses (except for financial and operating leases) respectively. IEA is Interest Earning Assets. LI and LE are Lease Income *and expenses and DI is dividend income. All variables used to measure Interest, Lease and Dividend Component (ILDC). OOI and OOE are Other Operating Income and expenses, FI, and FE are financial income and expenses. These variables are used to measure of Services Component (SC). Financial Component (FC) is sum of net profit or losses trading book with net profit or losses banking book. We measure business indicators (BI) as proxy for operational risk based it.*

The BI uses absolutes values to avoid counterintuitive results, and this index reduces the weight of components associated with activities less exposed to OR, and increases the weight of components associated with activities more exposed to OR (PWC, 2015).

Our primary concern lies in studying the linkage between OR and banking stability. We used a regression data panel of Iranian banks and a linear econometric model, where we controlled for economics variable (EV) and bank characteristic (BC) that have an effect on banking stability. This regression is indicated in Equation 2:

$$Z - score_{i,t} = \alpha_0 + \alpha_1 BI_{i,t} + \alpha_2 BC_{i,t} + \alpha_3 EV_{i,t} + \varepsilon_{i,t} \qquad (2)$$

where the subscripts of i and t indicate bank and time respectively, and $\varepsilon i,t$ is the error term with E(εi,t)=0 for all *i*s and *t*s. In Equation 2, the dependent variable is Z-score. Banking stability is measured by Z-score and size. Z-score represents variable that is an agent for business disruption and system failures or banking stability. According to the approach proposed by Roy (1952), Blair and Heggestad (1978), this variable is inversely related to the probability of default. It is denoted as follows:

$$Z = (ROA+EA) / \sigma (ROA) \qquad (3)$$

where ROA is the rate of return on assets (ratio of pre-tax profit to total assets), EA is the ratio of equity to assets, and σ (ROA) is an estimate of standard deviation of the rate of return on assets. A higher Z indicates that a bank is farther from insolvency. Since Z is highly skewed, we use its natural logarithm that is normally distributed. Z-score is the number of standard deviation units by which profitability will have to decline before bank capitalization is depleted (Roy, 1952). Z-score increases with higher profitability and capitalization levels but it reduces by unstable earnings in higher standard deviation of return on assets. A higher Z-score implies that a bank is farther from default and hence is more stable. A Z-score increase indicates a decrease in banks' probability of bankruptcy. For reasons of asymmetry, we use the log of the Z-score as in Houston et al. (2010).

The main problem in empirical work is heteroscedasticity focused on the standard instrumental variables, because the estimates of the standard errors are inconsistent and prevent valid inference. The usual approach today when facing heteroskedasticity of unknown forms is to use the system generalized method of moment (System GMM). Given that GMM considers the unobserved effect transforming the variables into first differences, we use this technique as an effective tool to deal with endogeneity problems. Arellano and Bover (1995) proposed the use of GMM that bypasses the finite sample bias if one assumes mild stationarity on the initial conditions of the underlying data generation process. This method provdes estimates that have higher levels of efficiency and consistency, and allows for the introduction of highly persistent variables such as bank and country controls. Tests by Hansen/Sargan were estimated to measure the model specification validity. This test examines the lack of correlation between the instruments and the error term.

$$Z-score_{i,t} = \alpha_0 + \alpha_1 Z-score_{i,t-1} + \alpha_2 BI_{i,t} + \alpha_3 BC_{i,t} + \alpha_4 EV_{i,t} + \varepsilon_{i,t} \qquad (4)$$

Bank attributes include liquidity ratio, capital adequacy and capital ratio, deposit ratio, nonperforming loan, non-interest ratio and ratio cost, and the return on asset. Liquid ratio (LIQUID) refers to the ratio of liquid assets including trading asset over total bank assets. Kohler (2014) showed evidence that banks with a larger ratio of liquid assets to total assets were more stable. Capital is the rate of fund available to support the bank's risk. This paper expected the coefficient of this variable to be positive (like Athanasoglou, 2011; Lee and Hsieh, 2013). Berger and Bouwman (2013) also provided evidence that the survival probability of US banks in market and banking crises increased with better capitalization. Deposit ratio (DR) shows the bank's leverage structure and its degree of risk-taking. Gropp and Heider (2009) argued that the non-deposit funding alone, made banks vulnerable to distress, but deposits were a more stable funding in the banking system that decreased crisis. Nonperforming loans (NPL) can lead to efficiency problem for the banking sector. Several studies focused on the nonperforming loans as the metrics to assess the vulnerability of the financial system over time. Non-interest income (NON.I) is a way of making revenue and ensuring liquidity in the event of increased rates. Altunbas et al. (2011) and Liikanen (2012) proposed that a fee and commission income decreased banking stability. One explanation for this effect is the unstable nature of non-interest income and the possibility that it will decline more during the times of market distress. Esterhuysen et al. (2011) showed that cost ratio (CR) had a more stable situation in EU banks than non-interest income before and after the crisis, and inflation and GDP growth were the macroeconomic parameters, which will be inserted into the models in the present paper.

We use dummy variables in order to indicate four types of banks in our sample, including private banks, state banks, privatized banks, and specialized banks. Each dummy variable would be equal to 1 if the bank belongs to one of the four types mentioned in our sample, and D1, D2, D3, and D4 represent each dummy variable. We estimate the effect of bank type on banking stability by multiplying dummy variables by bank business indicator.

Many reasons lead to the increased importance of OR, one of which is the increasing complexity of financial assets and trading procedures (Chernobai et al., 2011). Some of financial studies on bankruptcy deal mainly with the fact that large and complex financial institutions face a crisis and instability. Knaup and Wagner (2012) found that size had a critical role in a financial shock. Specified the increased size and complexity of the banking industry, OR intensifies system-wide risk levels, and has a greater potential to emerge in more harmful ways than many other sources of risk (Chernobai et al., 2021). Although OR always has been existed as one of the primary risks in the financial industry, lacking corporate governance and systemic risk from financial derivatives may increase adverse outcomes resulting from the organization of failed business activities, inadequate internal processes, failed information systems, delinquency by people, and other unforeseen external events. In addition, Muriithi and Waweru (2017) showed that bank size had an effect on the internal and external fraud in Kenya, and increase OR. Size is measured by the logarithm of total assets and the regression equation described in Equation 5:

$$Z - score_{i,t} = \alpha_0 + \alpha_1 Z - score_{i,t-1} + \alpha_2 BI_{i,t} * size_{i,t} + \alpha_3 BC_{i,t} + \alpha_4 EV_{i,t} + \varepsilon_{i,t} \quad (5)$$

3.1 Data and Statistics Summery

The banking industry in Iran consists of 35 banks, including three state banks, five specialized banks, twenty private banks that are listed in the stock exchange, and four financial institutions that are supervised by the central bank. In Iran, bank OR events occur frequently. The central bank of Iran is the regulatory authority that has issued a document in 2006 on OR titled “guidelines for OR management”. The central bank of Iran ordered all Iranian banks, especially active and large ones, to follow this regulation and establish an information system that records their internal OR events. In this paper, we collect OR data from the financial statement and other information that banks report to the central bank of Iran[1]. We use data from 30 banks to estimate models in the period of 10 years (2006–2015) into panel data, and thus overcome the degree of freedom problems. This research uses the OR measure based on BIS.

Table 1. Descriptive Statistics

Variables	**Mean**	**Stdev**	**Median**
Z-score	49.77	44.065	34.52
BI	4.52	0.735	4.01

1. Monthly data report of banks to the central bank of Iran, which has been received through correspondence with the central bank for the purpose of conducting research.

Variables	Mean	Stdev	Median
Cost ratio (CostR.)	0.596	0.2803	0.642
Capital adequacy ratio (CAR)	0.181	0.871	0.068
Deposit ratio (DR)	0.665	0.201	0.722
Non-Performing Loan (NPL)	0.128	0.1017	0.119
Size	5.153	0.582	5.232
Liquid ratio (Liquid)	0.238	0.132	0.218
Non.Income ratio (Non.I)	0.445	0.307	0.3095
Inflation (Inf.)	20.724	7.395	21.5
GDP growth rate	0.5203	1.04	0.3795

Source: Research Finding.

Table 1 shows the statistical characteristics of bank variables that we use in the model. All bank variables have been winsorized at the 1% and 99% percentiles to reduce the influence of outliers and potential data errors. The mean Z-score is equal to 49.77, and the mean BI is equal to 59.8. The mean of the other variable is less 1, and the mean implicit size is even larger at 5.15. The average inflation is equal to 20.72.

Table 2 provides the correlation coefficients between all variables that are used in the models. Z-score is negatively correlated with bank size and negatively correlated with the inflation. Among the pairs of bank specific variables, the bank size indicates the moderate negative correlation with fee income and strong negative correlation with bank equity. The BI index is negatively correlated with cost ratio and nonperforming loans. This index has a negative correlation Z score.

Table 2. The Correlation Matrix of Variables

Variables	BI	Cost ratio	Capital ratio	Deposit ratio	NPL	Size	Liquid	Non. I.	Inf.	GDP growth	Z score
BI	1										
Cost ratio	0.579	1									
Capital ratio	-0.4179	-0.1152	1								

Variables	BI	Cost ratio	Capital ratio	Deposit ratio	NPL	Size	Liquid	Non. I.	Inf.	GDP growth	Z score
Deposit ratio	0.1512	0.6922	-0.626	1							
NPL	-0.0577	0.1802	-0.283	0.1885	1						
Size	0.865	0.01182	-0.409	-0.0501	0.2535	1					
Liquid	0.3916	0.10893	0.4899	0.10793	-0.0664	0.1424	1				
Non. Interest Income	0.5391	0.41499	0. 856	0. 1676	0.10183	0.10751	0.07992	1			
Inflation	0.5675	0.16248	0. 597	0. 1373	0.0641	-0.0371	0.11993	0.2381	1		
Gdp growth	-0.6097	0.04889	-0. 199	0. 9117	0.11723	0.04873	-0.0392	0.01637	0.392	1	
Z score	-0.4503	0.01899	0.6789	0.3978	0.44797	0.27461	0.5243	0.16513	0.24651	0.2292	1

Source: Research finding.

It is necessary to test unit root of all applied variables in estimations because unit root variables have quasi regression problem for both time series data and panel data. Therefore, Levin-Lin-Chu, Im-Pesaran-Shin W-stat test, Fisher, and Hadri test are used to study common unit root of variables. Results are provided in Table 3.

Table 3. The Result of Unit Root Test of Variables

Variables	Levin, Lin and Chu test,	Im, Pesaran and Shin w-stat test	PP -Fisher Chi-square	ADF - Fisher Chi-square
BI	-15.837 (0.000)	-3.742 (0.0001)	44.99 (0.0012)	53.39 (0.000)
Cost Ratio	-1.45 (0.000)	-3.476 (0.000)	122.88 (0.000)	83.83 (0.000)
CAR	-6.598 (0.000)	-2.696 (0.000)	135.39 (0.000)	71.103 (0.000)
Deposit Ratio	-7.774 (0.000)	-2.73 (0.000)	152.02 (0.000)	69.31 (0.000)
NPL	-12.133 (0.000)	-3.491 (0.000)	68.603 (0.000)	66.002 (0.000)
Size	-10.152 (0.000)	-5.122 (0.000)	197.18 (0.000)	103.86 (0.000)
GDP growth	-8.12024 (0.000)	-4.329 (0.000)	66.306 (0.006)	88.309 (0.000)
Liquid	-13.1815 (0.000)	-3.321 (0.000)	157.406 (0.000)	75.64 (0.000)
Non.I	-15.157 (0.000)	-4.983 (0.000)	165.506 (0.000)	98.54 (0.000)
Inf.	-14.72 (0.000)	-3.261 (0.000)	92.31 (0.000)	95.47 (0.000)

Source: Research finding.

Note: Cost ratio (CR) is total operating costs (excluding bad and doubtful debt charges) to total income (the sum of net interest and non-interest income); Deposit ratio (DR) is the ratio of deposit over total bank assets. NPL is non-performing loans to total loans; Size is logarithm of total asset; Liquid is the ratio of liquid assets include trading asset over total bank assets; Non-interest income (NON.I) is bank and creditor income derived primarily from fees and other non-income in banks; in addition, Capital Adequacy (CAR).

3.2 Empirical Results

Table 4 presents the results of the estimation in Equation 3. Column 1 in this table shows the estimates of panel data using ordinary least squares (OLS). Colom 2 provides the estimates of the equation by using random effect. Panel OLS regression method use both fixed and random effects. The Hausman specification test verifies the condition on zero correlation between individual effect and explanatory variables. According to the Hausman test, random effect is used to estimate the regression model. Columns 3, 4, 5, and 6 show the GMM estimator that has been tested by Sargan test.

Table 4. Estimation of Regression Model

Variables	OLS Estimation	Fixed/ Random Effect	GMM Estimation			
	Z-score	Z-score	Z-score			
			(1)	(2)	(3)	(4)
Z-score (-1)	---	---	0.6581 (2.41)	0.3991 (1.79)	0.5698 (1.84)	0.4598 (3.89)
BI	-1.598 (-2.21)	-1.693 (-2.32)	-1.24 (-1.83)	-0.84 (-1.89)	-0.98 (-2.78)	-0.704 (-2.71)
CostR.	2.024 (2.001)	2.1698 (1.68)	4.144 (2.489)	---	---	4.458 (1.854)
CAR	2.425 (1.95)	1.991 (2.598)	2.237 (2.584)	4.487 (3.255)	3.569 (2. 11)	3.115 (2.025)
DepositR.	0.3691 (2.54)	0.435 (1.785)	0.569 (1.71)	0.698 (1.69)	0.698 (1.25)	---
NPL	-0.992 (-2.22)	-1.223 (-3.012)	-0.934 (-2.344)	-1.012 (-2.65)	---	-0.8996 (-1.91)
Size	2.69 (2.602)	2.289 (2.98)	2.69 (3.36)	---	---	2.81 (3.114)
Inflation	-0.1458 (-1.77)	-0.4458 (-1.92)	-0.1698 (-1.82)	-0.1981 (-2.52)	-0.925 (-2.33)	-0.599 (-1.74)
GDP growth	---	---	---	---	---	1.698 (1.99)
AR(1)	0.956 (2.14)	---	---	---	---	---
R^2	0.89	0.85	0.89	0.79	0.76	0.77
D.W	2.15	2.36	---	---	---	---
Hausman- Test	---	29.55	---	---	---	---
Prob.	---	0.000	---	---	---	---
Sargan Test	---	---	35.26	39.44	33.56	38.69
Prob.	---	---	0.22	0.35	0.17	0.31
AR(1)	---	---	-1.741 (0.05)	-2.58 (0.0457)	-1.891 (0.038)	-1.5784 (0.023)
AR(2)	---	---	-1.446 (0.548)	-1.834 (0.487)	-1.702 (0.650)	-1.622 (0.691)

Source: Research Finding.

Note: Cost ratio (CR) is total operating costs (excluding bad and doubtful debt charges) to total income (the sum of net interest and non-interest income); Deposit ratio (DR) is the ratio of deposit over total bank assets. NPL is non-performing loans to total loans; Size is logarithm of total asset; in addition, Capital Adequacy (CAR) is another variable.

Dynamic relations contain lagged variables, and because of such variables and heterogeneous sectoral effects, autocorrelation problem will occur. In addition, the GLS estimator is based on random effects for dynamic pooling data. Therefore, Arellano and Bond (1991) proposed a new approach, which processed from GMM. In this method, Arellano and Bond represented two-step GMM estimator, and the validity of matrix tools was tested by Sargan test. In Sargan test, the null hypothesis indicates that matrix tools do not correlate with lagged variables. As can be seen, the null hypothesis is not rejected. Therefore, matrix tools do not correlate with lagged variables, and the applied tools have necessary validity for estimation.

We do not reject the null that the additional moment conditions are valid. The values reported for Arellano-Bond test for second order serial correlation are the p-values for second order auto correlated disturbances in the first-differenced equation. For the Arellano- Bond tests, the coefficient estimation of AR (1) should be significant and AR (2) statistic is not significant that this concept shown in the tables.

Table 4 shows the estimation results of panel regression for Z-score and OR in the Iranian banking system. The coefficients of the BI are -0.883 in OLS estimation. This coefficient shows a negative significant relationship with banking stability. The results indicate that more BI creates the lower Z-score. In addition, except NPL and inflation, other control variables have a positive significant relationship with the banking stability index.

Columns 3, 4, 5, and 6 report the results of estimation model with the dynamic system GMM. The coefficient of lagged Z-score (significant at the 1% level) shows that the dynamic effect is a good choice in explaining. According to GMM estimator, we find that the coefficient of BI is negative and statistically significant at the 1% level. That is, BI significantly affects banking stability. All of these results confirm the hypothesis that OR will be effective on stability. According to the results, the increased OR has led to a reduction in banking stability.

The capital ratio has a positive relationship with banking stability. Deposit ratio has also a positive significant relationship with banking stability. Deposit ratio plays the main role in the balance sheet, and affect passively on banking stability that is confirmed by Gropp and Heidar (2009). Cost ratio has a positive relationship with banking stability. So, the bank management can decrease costs by increasing efficient and corporate governance. The nonperforming loan has a negative effect on banking stability. Nonperforming loans increase the credit risk and thus leads to decrease banking stability.

Inflation in all three models has a negative significant relationship with the Z-score. Demirgüç-Kunt and Detragiache (2005), Giavazzi and Giovannini (2010), and Frankel (2012) claimed that inflation was responsible for increased risk and the cause of the crisis. Unlike research such as Borio and Lowe (2004) studies e.g. Altunbas et al. (2011), Kohler (2013), Karminski and Kostrov (2014) confirmed that size had a positive significant relationship with Z-score. The positive relationship between size and stability has been explained by the better abilities of large banks to diversify their risks, compared to small banks, and to keep the stability in the bank. According to the results, the coefficient size is positive and significant in the Iranian banking system.

3.3 Robustness Checks

In this section, we present the results of a set of robustness checks. Then, we focus on two types of robustness checks. First, we analyze the result by separating the banks type in the Iranian banking systems. In our analysis, we consider dummy variables for different types of banks. Second, the set of robustness check includes the results of the banking size in the model.

In the Iranian banking system, there are four types of banks (private, state, privatized, and specialized). Different structures of these banks have an important impact on banking stability. D1 is equal to 1 if the bank is private and zero otherwise. D2 is equal to 1 if the bank is state and zero otherwise. D3 is equal to 1 if the bank is privatized and zero otherwise. D4 is equal to 1 if the bank is specialized and zero otherwise. By multiplying these variables by the business indicator, one can distinguish different banks types according to their effect on banking stability. We add to our benchmark model also variables that indicate the bank type in system. The estimates of this process are indicated in Table 5.

Table 5. Estimation of Regression Model Focused on Ownership of Bank

Variables	GMM Estimation			
	Z- score	Z- score	Z- score	Z- score
Z-score (-1)	0.7658 (1.95)	0.8541 (1.87)	0.6598 (1.69)	0.5996 (2.02)
CR	2.165 (2.035)	1.968 (2.087)	2.265 (2.078)	---
CAR	2.121 (2.013)	2.098 (2.112)	---	3.589 (2.214)
DR	3.224 (1.918)	3.517 (1.865)	3.512 (1.902)	3.698 (1.998)
NPL	-1.992 (-2.24)	-1.918 (-2.55)	-1.605 (-2.29)	-1.687 (-2.16)
Inf.	-0.0916 (-2.011)	-0.0812 (-2.101)	-0.0715 (-2.115)	-0.0811 (-1.99)
GDP growth rate	0.881 (1.93)	0.976 (1.98)	0.766 (1.809)	0.556 (1.768)
$\mathbf{D_1 \times BI}$	-2.31 (-1.73)	---	---	---
$\mathbf{D_2 \times BI}$	---	-2.608 (-1.88)	---	---
$\mathbf{D_3 \times BI}$	---	---	-2.557 (-1.714)	---
$\mathbf{D_4 \times BI}$	---	---	---	-2.852 (-2.511)
$\mathbf{R^2}$	0.83	0.91	0.73	0.89
Sargan Test	38.47	36.69	37.11	38.55
prob	0.24	0.21	0.25	0.22
AR(1)	-0.141 (0.041)	-0.95 (0.051)	-2.141 (0.041)	-2.98 (0.031)
AR(2)	-1.126 (0.641)	-2.136 (0.691)	-3.121 (0.441)	-1.132 (0.481)

Source: Research finding.

Note: Cost ratio (CR) is total operating costs (excluding bad and doubtful debt charges) to total income (the sum of net interest and non-interest income); Deposit ratio (DR) is the ratio of deposit over total bank assets. NPL is non-performing loans to total loans; in addition, Capital Adequacy (CAR) is another variable.

According to the results, the private bank dummy variable multiplied by BI has a negative effect on banking stability. In addition, the coefficient of multiplied privatized bank dummy variable (D3) and BI is negative. Therefore, private and privatized banks have a negative impact on banking stability. On the other hand, the coefficient of state bank dummy variable and specialized bank dummy variable is negative. Therefore, the state and specialized banks have a negative effect on earnings volatility.

This instrument is technically important for Arellano-Bond model. We also indicate that the several types of estimation method shows the same results. We apply the standard panel OLS approach with fixed and random effects.

Table 6. Estimation of Regression Model Focused on Size of Bank

Variables	**OLS Estimation**	**Fixed/ Random Effect**	**GMM Estimation**			
	Z-score	**Z-score**	**Z-score**			
			(1)	**(2)**	**(3)**	**(4)**
Z-score (-1)	---	---	0.889 (1.93)	0.661 (2. 87)	0.772 (2. 08)	0. 756 (2.62)
Size × BI	-0.5102 (-3.204)	-0.565 (-3.453)	-0.578 (-3.096)	-0.689 (-3.113)	-0.623 (-3.611)	-0.677 (-3.298)
CAR	2.89 (2.708)	2.947 (2.209)	3.501 (3.587)	3.112 (3.68)	2.987 (2.489)	3.467 (2.118)
GDP Growth rate	0.7078 (2.523)	0.7701 (1.391)	0.8254 (2.23)	0.981 (2.632)	0.728 (2.801)	0.6998 (2.401)
Liquid	4.402 (3.0089)	3.961 (3.025)	3.65 (3.289)	4.725 (3.369)	4.801 (3.601)	3.568 (3.55)
No. Interest	2.55 (3.728)	2.369 (5.089)	3.08 (2.1089)	---	2.14 (2.456)	2.698 (2.902)
Inf.	-0.0954 (-2.44)	-0.2147 (-1.94)	-0.1458 (-2.81)	-0.1267 (-3.72)	-0.092 (-2.37)	-0.0815 (-2.69)
R^2	0.74	0.81	0.82	0.78	0.73	0.74
D.W	2.21	2.091	---	---	---	---
Hausman-Test	---	44.3	---	---	---	---
Prob.	---	0.000	---	---	---	---
Sargan Test	---	---	9.95	9.105	9.701	9.48
prob	---	---	0.29	0.31	0.29	0.27
AR(1)	---	---	-1.143 (0.05)	-2.58 (0.0457)	-1.901 (0.038)	-2.538 (0.023)
AR(2)	---	---	-2.406 (0.746)	-1.134 (0.581)	-2.713 (0.458)	-2.602 (0.892)

Source: Research Finding.

Note: Liquid is the ratio of liquid assets include trading asset over total bank assets; Non-interest income (NON.I) is bank and creditor income derived primarily from fees and other non-income in banks; in addition, Capital Adequacy (CAR) and Return of asset (ROA) are the other variables.

Table 6 shows the results of the relationship between Z-score and size of the Iranian banks in the equation. We used the interaction of size and BI index variable to investigate the effect of size on stability by considering OR. The results show that Size × BI has a negative significant relationship with the Z-score. According to the results of Table 6, the size alone has a positive significant relationship with stability, but Size × BI variable has a negative significant coefficient. The coefficient of Size × BI variable in GMM model is almost 0.40 and statistically significant at the 1% level, suggesting that the increase in variable can create less banking stability.

4. Conclusion

Literature evidence show that OR and each of its events can increase banking instability. Failure to manage OR in banking can be the beginning of the financial crisis and recently, inside of credit, market and liquidity risks, OR has been recognized as the main source of failures in financial institutions. This paper analyzed the relationship between OR and banking stability by a panel data of Iranian bank over the period 2005–2015. In addition, we used the panel OLS regression in fixed and random effects, and dynamic panel data (GMM) indicated the relationship. We used the dynamic GMM system estimator that was useful to control for unobservable heterogeneity and potential endogeneity of bank-level variables. In addition, we used dummy variables in order to indicate types of banks, which were in our sample, including private banks, state banks, privatized banks, and specialized banks.

We calculated OR measure based on AMA and BI according to the guideline by BCBS (2017). It was found that the size of banks had a critical role in a financial crisis and shock in the Iranian banking system. The increased size can affect the OR intensification and the banking instability. Therefore, in a separate model, we studied the effect of size and OR on banking stability. The results showed a negative significant (at the 1% level) relationship between OR and Z-score in the Iranian banking system. In other words, the increased OR leads to a decrease in banking stability. These studies revealed that OR could lead to collapse and instability. The investigation of the combined effect of size and OR on Z-score also indicated a negative significant relationship. In other words, the complexity and breadth of the bank have the potential to increase the OR, both affecting the banking instability.

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