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Original Research Article

Does the Merger of Banks Reduce Operational and Market Risk?

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The objective of banks' policymakers is risk management. Merging of banks is a method to improve risk management. Operational risk and market risk are two of the most crucial risks for banks, serving as the foundation for other risks. Therefore, the management of these risks is important. Iran merged five banks in 2017. One of the concerns of this program's administrators and banking researchers is whether the merger of banks can enhance the management of operational risk and market risk. To answer this question, this article investigates the short- and long-term effects of bank mergers on operational risk and market risk using the Autoregressive Distributed Lag (ARDL) model. To measure operational risk and market risk, we used the Basel Committee's guidelines and Sepah Bank's financial statement data for 2011-2022. For the purpose of measuring the integration of banks, a dummy variable has been considered, during the 2011-2017 that it is one and it is zero before 2011 and after 2017. Results indicate the merger of banks increases operational risk in the short- and long-term, while market risk increases in the short-term and decreases in the long-term. Investing in assets ratio has little impact on operational risk, but can reduce market risk. The relationship between the increase in deposit interest rate and operational risk is negative, while there is positive relationship between market risk and deposit interest rate.

Keywords: Merger, Operational Risk, Market Risk, Autoregressive Distributed Lag (ARDL) Model.
JEL Classification: C59, G21, G22.

1 Introduction

The phenomenon of banks merger as well as financial and credit institutions merging has a lengthy history, dating back to the turn of the twentieth century

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(Rezitis, 2006). In this procedure, the assets and liabilities of two or more banks are merged into a single bank. This framework consists of three major phases: the strategy phase, the review and negotiation phase, and the final phase, which encompasses the completion of the integration process (Rezaee, 2011). One of the most significant objectives of bank mergers is risk management improving. Operational risk is the foundation of all other risks, and market risk is the most significant risk associated with operational risk.

The Basel Committee defines operational risk as the risk of loss resulting from inappropriate or incompetent processes, people, or systems, or from external events. Banks may be exposed to operational risk due to changes in the financial market, the macro-economy, and the global economy. Today, operational risk and its method of management are among the most essential topics in the banking industry. The prospective effects of this type of risk on the performance of banks and other financial institutions can sometimes be so severe as to result in their failure. Experts and relevant authorities have begun extensive efforts to identify and effectively manage this risk due to its potential effect.

Market risk occurs as a result of the effect of asset price fluctuations in the market. Individuals and organizations store their assets in a variety of forms, including cash, securities, bonds, real estate, gold, and other valuable assets. All of these assets are susceptible to price fluctuations, which are the primary source of market risk. In the majority of bankruptcies, market risk, one of the primary risk factors, plays the most significant role. The repeated and continuous financial crises caused by financial risk that have occurred in different parts of the globe over the past two decades have increased the need for quantitative and integrated financial risk management with a focus on market risk.

Mehr Eghtesad, Ghavamin, Hekmate Iranian, and Kowsar banks are merged with Sepah Bank in 2017. It is essential to examine the effects and consequences of the merger between these banks. Whether the merger of institutions can reduce operational risk and market risk is a fundamental question. To answer this question, the effect of the merger of the aforementioned banks on Sepah Bank's operational risk and market from 1996 to 2022 has been investigated. A dummy variable was used to define the bank integration index. Thus, during 2017-2022, the dummy variable is set to 1 and for the period prior to 2017, it is set to 0. For measuring operational risk and market risk, the Basel Committee's documents have been used. Thus, the BIA method was utilized to measure operational risk, whereas the net open position was utilized to measure market risk.

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In this article, it is essential to examine the short- and long-term effects of bank mergers on operational risk and market risk. To examine the impact of bank mergers on operational risk and market risk, we employ the Autoregressive Distributed Lag (ARDL) model. On the other hand, the unit root test reveals that certain independent variables are stationary after one difference. Therefore, it is necessary to employ the ARDL model.

The remainder of this paper is organized as follows. Section 2 presents the theoretical literature on operational risk and market risk and how to measure them. In Section 3, studies pertinent to the topic of this paper are discussed. Section 4 provides the sample and variables. In Section 5, the model is described in detail, and in Section 6, the required tests are specified. Section 7 contains the results and findings and, finally, Section 8 concludes the results.

2 Operational and Market Risk Theories

2.1 Operational Risk

Operational risk events have diverse origins, including transaction and execution errors, fraud, improper business practices, product defects, technology failures, employment discrimination, natural disasters (or ‘acts of god’), and terrorism (Cruz, 2002: 14; Jongh et al., 2013). Basel II defines operational risk as the risk of loss due to inadequate or failed internal processes, people, and systems or external events (BCBS, 2006; Jongh et al., 2013). This definition excludes reputational and strategic risk, but incorporates legal risk. Note that operational risk typically focuses solely on losses, as opposed to market risk, which also considers profits (Jongh et al., 2013).

Operational risk is the risk of loss resulting from insufficient or inappropriate internal processes, people, and systems (deficient IT background), and external events (Grdošić, 2016). Legal risk, is the risk of losses of lawsuits or penalties arising from legal, administrative, and other proceedings, and from the violation of contractual or legal obligations, and it is also a component of operational risk. Compliance risk includes the risk of future losses from the imposition of measures and penalties, the risk of future losses from the failure of operations to comply with regulations, standards, codes, internal rules, anti-money laundering and terrorism. Operational risk is the possibility of actual loss or incorrect profit presentation due to errors in data entry, data processing, evaluation, and posting (Grdošić, 2016).

The Basel Committee for Banking Supervision (2003) announced potential operational risk identification and evaluation tools in 2003. Tools are: self-assessment or risk assessment, risk mapping, risk indicators, and measurement.

- Self-assessment or risk assessment
  Using this tool, each bank evaluates its operations and activities in relation to the catalogue of potential operational risk exposures. This process is conducted internally and frequently includes checklists and/or workshops to identify the operational risk environment's strengths and weaknesses. Scorecards, for instance, are a great method to translate qualitative assessments into quantitative metrics that provide a relative rating of the various types of operational risk exposure. Some scores may pertain to risks inherent to a specific business activity, whereas others may evaluate risks that arise from a variety of business activities. Scores represent the inherent risks and the control implemented to mitigate them.
- Risk mapping
  Various business entities, organizational functions, and business flows are categorized according to the type of risk during this procedure. This task can identify areas of deficiency and assist the administration in establishing priorities for any future activities.
- Risk indicators
  Risk indicators are statistical and/or metric data, typically financial, that can shed light on the bank's risk position. The bank typically reviews these indicators on a monthly or quarterly basis to identify any changes that may be indicative of a risk-related problem. Examples of such indicators include the number of failed transactions, employee turnover rates, and the prevalence of errors and omissions.
- Measurement
  Some banks have begun to quantify their operational risk exposure using various methodologies. For example, data on the bank's historical loss experience can provide crucial information for assessing the bank's exposure to operational risk and formulating a strategy to reduce or control the risk.

2.2 Market Risk

The unpredictability associated with market dynamics compels banks to focus on market risk management. In this regard, banks improve and develop new methods to counteract these effects and to more accurately estimate interest rate risk, exchange rate risk, and other categories of risk (Trenca et al., 2015). The effects of the recent financial crisis served as a signal to the authorities that they must increase their capital to adequately cover these risks. As a result,

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the Basel III Committee mandates additional capital requirements for the trading ledger. VaR is the most popular statistical method for quantifying the market risk associated with bank portfolios. It is a probabilistic indicator that expresses the potential maximum loss of the portfolio's market value at a specific moment, taking into account a predetermined confidence level. VaR can be calculated using the historical simulation method, the parametric method, or the Monte Carlo method. The historical simulation method quantifies the prospective value of the change in the current portfolio based on the historical fluctuations of the risk factors, using the empirical distribution of historical data and without making any assumptions regarding the returns distributions. The parametric method implies that the distribution of daily returns is normal. The primary disadvantage of this method is that it is unable to estimate significant losses due to the fact that distributions frequently have fat tails, which are characterized by a large number of unexpected events and do not follow a normal distribution (Trenca et al., 2015). The Monte Carlo method involves producing future price scenarios based on the volatility and correlations of the portfolio's assets. Then, for each scenario, the portfolio value will be computed and the final results of the simulation will be reported, either as a portfolio distribution or a specific risk measure (Trenca et al., 2015). The Basel Committee recommends calculating VaR with a confidence level of 99% and an instantaneous price shock equivalent to a 10-day price fluctuation (Trenca et al., 2015).

3 Literature Review

Various studies have investigated the factors influencing operational risk and market risk from various perspectives, while few studies have dealt with the relationship between bank mergers and operational and market risks. The results of some studies indicate that operational risk and market risk were among the most significant hazards for banks during the 2008 financial crisis (Jongh et al., 2013; Trenca et al., 2015). According to Wang et al. (2018) and Grdošić (2016), operational risk is caused by inadequate internal control processes, human error, and inadequate information systems. Chernobai et al. (2011), Helbok & Wagner (2006), and Mehmood, Sheraz, Mehmood, & Mujtaba (2017) have investigated the factors that influence operational risk. Among these factors are fraud and the number of employees, and GDP growth indicated that all three had a negative significant impact on operational risk, as well as the fact that banks with lesser equity/assets and profitability ratios are more susceptible to operational risk than other banks. In addition, banks with higher NPL and larger asset sizes are more susceptible to operational risk.

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Lin & Chang (2015) found that bank mergers have a positive impact on operational risk. The integration of banks can reduce operational risk by enhancing the information system, implementing intelligent processes, and minimizing human error. According to Trenca et al. (2015), high market volatility is correlated with rising exchange rates, rising interest rates, and declining financial securities.

Tanna & Yousef (2019) examined the impact of mergers and acquisitions (M&As) on the market or systematic risk of acquiring. The results indicate that acquirers' market risk (and, consequently, their cost of capital) tends to increase following a merger. So increased acquirer risk only occurs when the acquirer's ex-ante market risk is relatively modest compared to the market risk. They also demonstrate, cash payment agreements for publicly traded targets reduce acquirers' risk, whereas global or industry-wide diversification has no significant impact. On the other hand, serial acquirers face a significant increase in risk with each additional M&A.

Amihud et al. (2002) concluded that the impact on the total and systemic risk of acquiring banks is insignificant. So, they emphasize that regulators do not need to be concerned about the risk implications of cross-border mergers. Similarly, Mishra et al. (2005) found that non-conglomerate (bank with a bank) U.S. mergers had a negligible impact on the systematic risk of acquiring banks, while reducing their unsystematic risk (and hence total risk). Bozos et al. (2013) disclosed that large bank mergers not only increase acquirers' systematic risk, but there is also a tendency for the beta to rise immediately after deal announcements and remain relatively high for up to two years afterward. According to Casu et al. (2015), mergers between banks and securities firms increase total risk via higher levels of systematic and idiosyncratic risk.

Ekadjaja et al. (2021) examined the effect of mergers on banks' performance. The results show that prior to and after the merger, there was no difference in bank performance, credit level, operational level, or capital level. Ahmadyan (2020) investigated the influence of bank mergers on financing. She examined banks in terms of their scale and health. The results indicated that the merger of small banks with large banks and the merger of healthy banks had a more positive impact on the supply of facilities than other alternatives.

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4 Sample and Variables

4.1 Sample

This study investigates the merger's effect on the operational and market risk of Iranian banks. In Iran, there are no investigations on this topic. For this reason, we decided to investigate the effect of mergers on the operational and market risk of Iranian banks from 1996 to 2022 using a sample of the Iranian banks from a developing nation.

As Sepah Bank has been merged with other banks (Mehr Eghtesad, Ghavamin, Hekmate Iranian, and Kowsar, we have used its financial statements. Since 2011, policymakers have proclaimed the merger of banks, and these banks merged in 2017. We employed a dummy variable to define the indicator of bank mergers, which has been 1 since 2017.

4.2 Variables

4.2.1 Dependent Variable

We estimate operational risk using the Basic Indicator Approach (BIA)[1], and market risk using the ratio of net open position in foreign exchange to capital.[2]

4.2.2 Explanatory Variables

This study's explanatory variables pertain to bank mergers. In 2017, the Mehr Eghtesad, Ghavamin, Hekmate Iranian, Kowsar, and Sepah banks merged, and a new Sepah Bank was established. In order to define the merger variable, a dummy variable has been created, with the value 1 representing the year that banks were merged.

4.2.3 Control Variables

Table 1 introduces control variables. The expression of control variables is based on experimental literature.

[1] Bank for International Settlements 2014. Consultative Document Operational risk –Revisions to the simpler approaches, Basel Committee on Banking Supervision.
[2] The international monetary fund, financial soundness indicators, 2019, compilation guide— Washington, D.C.: International Monetary Fund.

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Table 1
Control variables

Indicators	Variables
Capital Adequacy	capital ratio Z-score
Assets Quality	Loan Loss Provisions to Net Interest Revenue non-performing loans to loans
Management quality indicator	the ratio of interest expenses to total deposits Total Loans to Total Customer Deposit Operating non-interest revenue to asset income
Profitability	Return on average assets Net interest income to assets
Size	Log assets
External factors	GDP growth Inflation Exchange rate Deposit interest rate Credit interest rate Budget deficit Stock price

Source: Research findings

5 Model Specification

Greene (2008) defines ARDLs as standard least squares regressions that include delays of both the dependent variable and explanatory variables as regressors. Although ARDL models have been used in econometrics for decades, their popularity as a method for investigating long-run and co-integrating relationships between variables has increased in recent years (Pesaran & Shin, 1999).

An ARDL is a least-squares regression in which the dependent and explanatory variables comprise lags. ARDLs are typically denoted as $ARDL(p, q_1, \dots, q_k)$, where p represents the number of lags of the dependent variable, q_1 represents the number of lags of the first explanatory variable, and q_k represents the number of lags of the k^{th} explanatory variable. An ARDL is:

$$y_t = \alpha + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} X_{j,t-i} \beta_{j,i} + \epsilon_t \quad (1)$$

Some explanatory variables, X_j, may not contain any lagged terms in the model ($q_j = 0$). These variables are known as fixed or static regressors. Dynamic regressors are explanatory variables that include at least one lagged term. To specify an ARDL model, the number of lags of each variable must

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be determined (i.e. specify p and $q_1, \dots, q_k$ must be specified). These latency lengths can be determined using straightforward model selection procedures. Since an ARDL model can be estimated using least squares regression, standard Akaike, Schwarz, and Hannan-Quinn information criteria can be used to select the model. Alternately, the adjusted R^2 from the various least squares regressions can be utilized (EViews 9 User's Guide II).

In this paper, we develop two models. In the model (1), operational risk is the dependent variables, while market risk is the dependent variable in the second model. The first and second models are:

Model (1):

$$operational\ risk_t = \alpha + \sum_{i=1}^{p} \gamma_i operational\ risk_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} X_{j,t-i}\, \beta_{j,i} + \epsilon_t \quad (2)$$

Model (2):

$$market\ risk_t = \alpha + \sum_{i=1}^{p} \gamma_i market\ risk_{t-i} + \sum_{j=1}^{k} \sum_{i=0}^{q_j} X_{j,t-i}\, \beta_{j,i} + \epsilon_t \quad (3)$$

$X_{j,t-i}$ are control and explanatory variables.

5.1 Long-Run Relationships

Due to the fact that an ARDL model estimates the dynamic relationship between a dependent variable and explanatory variables, it is possible to convert the model into a long-run representation, revealing the long-run response of the dependent variable to a change in the explanatory variables. Long-run coefficients is:

$$\theta_j = \frac{\sum_{i=1}^{1j} \hat{\beta}_{j,i}}{1 - \sum_{i=1}^{p} \gamma_i} \quad (4)$$

Using the delta method (EViews 9 User's Guide II), the standard error of these long-run coefficients can be calculated from the standard errors of the original regression.

5.2 Co-Integrating Relationships

Traditional methods of estimating co-integrating relationships, such as the Engle-Granger (1987) or Johansen (1991; 1995) method, or single equation methods such as Fully Modified OLS or Dynamic OLS, either require all variables to be I(1) or require prior knowledge and specification of which variables are I(0) and which are I(1).

[DOI: 10.29252/jme.17.4. 485]

To address this issue, Pesaran & Shin (1999) demonstrated that co-integrating systems can be estimated as ARDL models, with the added benefit that the variables in the co-integrating relationship can be either I(0) or I(1) without the need to specify which variables are I(0) or I(1) beforehand.

Pesaran & Shin (1999) also observe that, unlike other methods of estimating co-integrating relationships, the ARDL representation does not necessitate symmetry of lag lengths; each variable can have a unique number of lag terms.

By transforming Equation 1 into differences and substituting the long-run coefficients from Equation 4, the co-integrating regression form of an ARDL model is obtained as Equation 5:

$$\Delta y_t = -\sum_{i=1}^{p-1} \gamma_i * \Delta y_{t-1} + \sum_{j=1}^{k} \sum_{i=0}^{q_j-1} \Delta X_{j,t-i} \beta_{j,i} * -\hat{\phi}\, EC_{t-1} + \epsilon_t \quad (5)$$

Where

$$EC_t = y_t - \alpha - \sum_{j=1} X_{j,t} \hat{\theta}_j$$
$$\hat{\phi} = 1 - \sum_{i=1}^{p} \hat{\gamma}_i$$
$$\gamma_i^* = \sum_{m=i+1}^{p} \hat{\gamma}_m$$
$$\beta_{j,i}^* = \sum_{i}^{q_j} \beta_{j,m} \quad (6)$$

Using the delta method, one can derive the standard error of the co-integrating relationship coefficients from the standard errors of the original regression.

6 Empirical Results

6.1 Unit Root Test

To determine whether our data are stationary, we use four varieties of Unit Root tests: augmented Dickey-Fuller, Elliott-Rothenberg-Stock DF-GLS, Phillips-Peron, Kwiatkowski-Phillips-Schmidt-Shin (LM test). Since the Elliott-Rothenberg-Stock (1996, Table 2) test can be cited for more than 50 observations, this article does not employ it. The null hypothesis in the augmented Dickey-Fuller and Elliott-Rothenberg-Stock DF-GLS and Phillips-Perron tests is that the variable has a unit root, whereas the null hypothesis in the Kwiatkowski-Phillips-Schmidt-Shin (LM test) test is that the variable is stationary. The null hypothesis fails the first three tests but passes the fourth.

Some variables are I (0) and others are I (1), so the ARDL model has been employed to investigate the impact of mergers on market and operational risk. The results indicate that the LM test is statistically significant at all three levels.

Table 2

Unit root tests

	Augmented Dickey-Fuller	**Elliott-Rothenberg-Stock DF-GLS**	**Phillips-Peron**	**Kwiatkowski-Phillips-Schmidt-Shin(LM test)**	**stationary**	
ROA	-4.104264 (0.0048)**	-4.165278 (0.004)**	-4.100226 (0.0048)**	0.213697	Level and Constant	I(0)
Size	-3.919294 (0.0347)**	-3.671492 (0.0015)**	-3. 561744 (0.0584)*	0.063392	Difference, constant, linear trend	I(1)
Net interest income to asset	-4.453898 (0.0022)**	-2.567564 (0.0179)*	-4.494578 (0.0020)**	0.285512	Level and constant	I(0)
Capital ratio	-4.609668 (0.0018)*,**,***	-4.822481 (0.0001) *,**,***	-8.920572 (0.0000) *,**,***	0.500000*	difference and constant	I(1)
Exchange rate	-2.960281 (0.0562)**	-2.997675 (0.0076)*	-2.960281 (0.0562)**	0.327439	difference and constant	I(1)
Deposit interest rate	-3.604145 (0.0174)*	-3.748643 (0.0074)*,**,***	-5.440769 (0.0003) *,**,***	0.314329	difference and constant	I(1)
Credit interest rate	-3.691983 (0.0133)*	-3.732947 (0.0015) *,**,***	-3.670421 (0.0139)**	0.165997	difference and constant	I(1)
Unemployment	-3.195563 (0.0347)*	-2.567251 (0.0184)**	-3.335343 (0.0261)**	0.142722	Level and Constant	I(0)
FDI	-2.991759 (0.0548)*,**,***	-2.435802 (0.0262)**	-2.082485 (0.2529)	0.283248	Level and Constant	I(0)
Zscore	-4.855094 (0.0010) *,**,***	-4.956900 (0.0001) *,**,***	-8.146206 (0.0000) *,**,***	0.500000	difference and constant	I(1)
Government deficit budget	-3.972021 (0.0098) *,**,***	-4.099389 (0.0011) *,**,***	-3.971539 (0.0098) *,**,***	0.108091	difference and constant	I(1)
Stock price	-5.858717 (0.0001) *,**,***	-6.032345 (0.0000) *,**,***	-5.737563 (0.0002) *,**,***	0.417117	difference and constant	I(1)
Non-performing loan to loan	-2.999365 (0.0505)***	-1.866474 (0.0760)***	-2.932051 (0.0577)***	0.101384	Level and Constant	I(0)
Loan Loss Provisions to Net Interest Revenue	-4.790306 (0.0010)*,**,***	-4.421325 (0.0002) *,**,***	-4.90985 (0.0010) *,**,***	0.218906	Level and Constant	I(0)

[DOI: 10.29252/jme.17.4. 485]

Interest expenses to deposits	-4.910877 (0.0013) *,**,***	-4.766397 (0.0002) *,**,***	-5.499706 (0.0004) *,**,***	0.279836	difference and constant	I(1)

* Significance at the level of 1 percent
** Significance at the level of 5 percent
*** Significance at the 10% level
Source: Research Findings

6.2 Bounds Testing

Pesaran, Shin, & Smith (2001) describe a method for testing whether the ARDL model contains a level (or long-run) relationship between the independent variable and the regressors using the co-integrating relationship form in Equation (5). The Bounds test procedure transforms Equation 6 into the representation shown below:

$$\Delta y_t = -\sum_{i=1}^{p-1} \gamma_i * \Delta y_{t-1} + \sum_{j=1}^{k} \sum_{i=0}^{q_j-1} \Delta X_{j,t-i} \beta_{j,i} * -\rho\, y_{t-1} - \alpha - \sum_{j=1}^{k} X'_{n,t-1}\, \delta_j + \epsilon_t \quad (7)$$

Consequently, the test for the existence of level relationships is merely a test of Equation 8:

$$\rho = 0$$
$$\delta_1 = \delta_2 = \cdots = \delta_k = 0 \quad (8)$$

Estimates of the coefficients used in the test may be derived from a regression using Equation 2 or directly from a regression using Equation 8. Under the null hypothesis (of no level relationships), the test statistic based on Equation 8 has a distinct distribution depending on whether the regressors are all I(0) or all I(1). Further, the distribution is non-standard in both instances. Pesaran, Shin, & Smith provide critical values for the cases in which all regressors are I(0) and the cases in which all regressors are I(1) and suggest using these critical values as bounds for the more common cases in which the regressors are a combination of I(0) and I(1).

The null hypothesis of Bounds Testing is No long-run relationship exists. As demonstrated in Table 3, the null hypothesis is rejected and a long-run relationship exists between the variables.

[DOI: 10.29252/jme.17.4. 485]

Table 3
Bounds Testing

Dependent variable	Test Statistic	Value	Result
Model (1)	F-Statistic	255.9607	The null hypothesis is rejected
Model (2)	F-Statistic	21.63788	The null hypothesis is rejected
Critical Value Bounds			
Significance	I(0) Bound	I(1) Bound	
10%	3.02	3.51	
5%	3.62	4.16	
2.5%	4.18	4.76	
1%	4.94	5.58	

Source: Research Findings

6.3 Normality Test

This view displays descriptive statistics regarding the residuals, such as the Jarque-Bera statistic for testing normality. If residuals have a normal distribution, the Jarque-Bera statistic should not be statistically significant. Under the null hypothesis of normally distributed errors, the Jarque-Bera statistic has a χ^2 distribution with two degrees of freedom. Table 4 demonstrates that errors in both models have a normal distribution.

Table 4
Normality test

Models	**Jaque-Bera (Probability)**
Model (1)	1.630126 (0.320535)
Model (2)	4.547034 (0.253636)

Source: Research Findings

6.4 Serial Correlation LM Test

Alternative to the Q-statistics for evaluating serial correlation. The test is a Lagrange multiplier (LM) test, a type of asymptotic (large sample) test. The null hypothesis of the LM test is that there is no serial correlation up to the specified lag order, p, where p is a pre-specified integer. The local alternative is ARMA(r,q) errors, where P=max(r,q) is the maximum number of lag terms. Note that this alternative incorporates both AR(p) and MA(p) error processes, allowing the test to be robust against a variety of autocorrelation structures. See Godfrey (1988) for further discussion. The null hypothesis is supported by Table 5, and there is no serial correlation.

[DOI: 10.29252/jme.17.4. 485]

Table 5
Breusch-Godfrey Serial Correlaion LM Test

Test	**F-statistic (Prob)**	**Obs*R-squared (Prob)**
Model (1)	33.91611 (0.9221)	17.81631 (0.0001)
Model (2)	25.41440 (0.1513)	15.65144 (0.0001)

Source: Research Findings

6.5 Heteroskedasticity Tests

The Breusch-Pagan-Godfrey test is a Lagrange multiplier test of the null hypothesis of no heteroskedasticity against heteroskedasticity of the form $\sigma_t^2 = \sigma^2 h(\acute{z}_t \alpha)$, where $\acute{z}_{t_{it}}$ is a vector of independent variables. Acceptance is given to the null hypothesis.

Table 6
Breusch-Pagan-Godfrey test

Test	**F-statistic (Prob)**	**Obs*R-squared (Prob)**	**Scaled explained SS (Prob)**
Model (1)	8.068267 (0.2703)	16.86068 (0.3273)	0.381727 (0.9857)
Model (2)	0.401055 (0.8648)	14.57691 (0.4823)	0.062503 (0.9999)

Source: Research Findings

6.6 Stability Diagnostics

Stability Diagnostics investigates the consistency of our model's parameters across subsamples of our data. The RESET test administered by Ramsey is one of the Stability Diagnostics. RESET is an acronym for Regression Specification Error Test, which Ramsey (1969) proposed. The output of the test includes the test regression, F-statistic, and log-likelihood ratio for evaluating the null hypothesis that coefficients on powers of fitted values are all zero. Rejecting the null hypothesis, the model is stable.

Table 7
Ramsey RESET Test

Test	**T-statistic (Prob)**	**F-statistic (Prob)**
Model (1)	3.516420 (0.1562)	4.748021 (0. 1562)
Model (2)	5.365534 (0.0615)	19.23183 (0.0615)

Source: Research Findings

7 Empirical Results

7.1 Dynamic Model

This paper investigates the effect of merger on operational risk and market risk using Lin and Chang (2015) and Ekadjaja et al. (2021). Due to the non-stationarity of some variables, the ARDL model is used to estimate the model. First, the short-term dynamic model is estimated. The outcomes are shown in Table 9. As can be seen from the results of the dynamic model, the estimated models have a high R^2, indicating that independent variables have a high capacity for explanation. The estimated models also provide the standard error assumptions. The dynamic model's results indicate:

The merger of banks can reduce operational risk and increase market risk at the beginning of a period, but after a few periods, it increases operational risk and decreases market risk. Generally, operational risk is defined as the consequence of human or technical errors and events. This risk consists of fraud (when merchants provide false information), management errors, and a lack of control. A technical error may be the result of a deficiency in transaction processing information, transfer systems, or any other organizational-level issue. In the early years, the merger of institutions was met with a number of difficulties and obstacles that posed a potential operational risk. Therefore, the merger of banks increases operational risk. As a state bank, Sepah Bank has limited freedom of action when accessing the currency market. Therefore, based on the form of market risk considered in this article, the merger of banks can reduce market risk due to fluctuations in exchange rates.

The Basel Committee defines operational risk as "the risk of loss due to inadequate or failed internal processes, people, or systems or external events."

This definition includes human error, fraud, malice, system malfunctions, personnel management issues, commercial disputes, accidents, fires, and floods. In other words, its preview appears so expansive that its practical application is not immediately apparent.

NPLs have a positive impact on operational risk and a negative impact on market risk. Nonperforming loans indicate that human and technical errors have occurred. Due to the lack of a suitable structure for the administration of the facility portfolio in Iranian banking, the supply of facilities is susceptible to a variety of common errors, which increases both credit risk and operational risk. However, the increase in credit risk and the restriction of a portion of the bank's assets in the community restrict the bank's ability to participate in market activities such as the foreign exchange market. Therefore, increasing credit risk decreases market risk.

Investing in assets ratio has no significant effect on operational risk, but it can mitigate currency-related market risk. The investment includes non-currency items, such as the stock market; the entry of banks into these areas diminishes the amount of capital available to enter the currency market.

The scale of a bank correlates positively and significantly with operational risk and market risk. So that increasing the bank's scale increases operational risk and market risk. There is a positive significant correlation between economic growth and operational and market risk. As economic growth improves, banks become more inclined to engage in high-risk, high-reward market activities, which can increase the operational risk. However, there is a negative relationship between inflation and operational risk and market risk. This result demonstrates the unsound structure of banks.

The relationship between the increase in deposit interest rate and operational risk is negative, while it is positive for market risk. On the one hand, an increase in the deposit interest rate increases the loan interest rate. Customers with high-yield plans are more likely to receive bank facilities if the credit interest rate is increased, thereby reducing both credit risk and operational risk. On the other hand, attracting more resources increases the bank's capacity to engage in market-related activities, thereby increasing market risk.

Table 8
Dynamic Model: ARDL (4,4)

	Model (1)*	**Model (2)****
Variable	Coefficient (t-Statistic) [Prob]	Coefficient (t-Statistic) [Prob]
Operational risk (-1)	0.626376	

[DOI: 10.29252/jme.17.4. 485]

	(10.58239) [0.0600]	
Operational risk (-2)	0.608894 (3.656301) [0.1700]	
Operational risk (-3)	0.491854 (4.836914) [0.1298]	
Operational risk (-4)	0.412449 (4.415820) [0.1418]	
Market risk (-1)		4.032037 (3.846272) [0.1619]
Market risk (-2)		0.367931 (2.051329) [0.2888]
Market risk (-3)		2.446164 (3.688183) [0.1686]
Market risk (-4)		1.546672 (1.905470) [0.3077]
merger	-5.666053 (-11.25219) [0.0564]	1.298468 (2.990339) [0.2054]
Merger (-1)	1.294487 (3.363438) [0.1840]	-6.186530 (-3.430086) [0.1806]
Merger (-2)	1.873390 (5.111420) [0.1230]	-3.273892 (-1.516779) [0.3711]
Merger (-3)	2.680765 (4.006324) [0.1557]	2.336077 (1.574849) [0.3602]
Merger (-4)	7.605116 (6.444426) [0.0980]	-1.244748 (-4.963540) [0.1266]
NPL	8.008034 (3.371982) [0.1835]	-2.229506 (-4.083439) [0.1529]
Investment to assets	-6.877292 (-1.031811) [0.4900]	-4.392892 (-2.973509) [0.2065]
Log assets	3.224118 (3.710917) [0.1676]	1.412161 (3.133023) [0.1967]

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GDP growth	1.873256 (2.986334) [0.2057]	1.589835 (1.264465) [0.4260]
inflation	-2.705236 (-2.976077) [0.2064]	-0.276975 (-1.309609) [0.4152]
Deposit interest rate	-2.001871 (-7.731806) [0.0819]	4.166633 (3.404391) [0.1819]
C	8.507550 (1.689300) [0.3403]	-3.143049 (-3.333658) [0.1855]
R-squared	0.979666	0.962806
Adjusted R-squared	0.954660	0.884904
Prob(F-statistic)	0.055482	0.053794

* Dependent variable is operational risk
** Dependent variable is market risk
Source: Research Findings

7.2 Long Run Model

According to Table 9, all coefficients of the variables are statistically significant and have the anticipated signs. As can be seen, bank mergers reduce market risk but increase operational risk over the long-run. Additionally, the size of a bank increases market risk and operational risk. Inflation decreases both operational and market risk, while GDP growth increases both of them.

Table 9
Long Run Form

	Model (1)*	Model (2)**
Variable	Coefficient (t-Statistic) [Prob]	Coefficient (t-Statistic) [Prob]
merger	2.482255 (3.551921) [0.1747]	-5.779298 (-1.381724) [0.3988]
NPL	2.5506759) (3.112749) [0.1979]	-0.353920 (-7.406367) [0.0854]
Investment to asset	-2.190518 (-1.051122) [0.4841]	-0.697344 (-3.754494) [0.1657]
Log of assets	1.026928 (4.686117) [0.1338]	2.241718 (4.633570) [0.1353]
GDP Growth	5.966594 (2.870708) [0.2134]	0.252376 (1.443493) [0.3857]
Inflation	-8.616571 (-3.411197) [0.1815]	-0.043968 (-1.525058) [0.3695]
Deposit interest rate	-6.376251 (-5.593359) [0.1126]	6.614270 (5.416591) [0.1162]
C	2.709779 (1.550131) [0.3647]	-49.89395 (-5.395632) [0.1167]

* Dependent variable is operational risk
** Dependent variable is market risk
Source: Research Findings

7.3 Co-integration Model

The existence of a long-run relationship between the approximated model's set of variables provides the rationale for employing an error correction model in which short-term fluctuations are related to equilibrium and long-term values. The error coefficient is estimated to be -0.080139 and -0.183706 in models one and two, respectively, according to Table 10. Thus, model one adjusts short-term imbalances by 0.08% per period, while model two adjusts 18% per period to achieve long-term equilibrium values.

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Table 10
ARDL Co-integrating

	Model (1)*	**Model (2)****
Variable	Coefficient (t-Statistic) [Prob]	Coefficient (t-Statistic) [Prob]
D(operational risk(-1))	1.480735 (24.964940) [0.0255]	
D(operational risk (-2))	0.884067 (21.712774) [0.0293]	
D(operational risk (-3))	0.396566 (13.376715) [0.0475]	
D(Market risk(-1))		1.261251 (13.697770) [0.0464]
D(Market risk (-2))		0.877810 (12.158903) [0.0522]
D(Market risk (-3))		-1.489268 (-15.153770) [0.0419]
D(merger)	-5.696870 (-4.160675) [0.0153]	1.262142 (2.164005) [0.0301]
D(merger (-1))	-1.192254 (-2.803695) [0.0227]	10.289495 (2.506438) [0.0283]
D(merger (-2))	-1.005107 (-2.439105) [0.0262]	9.923864 (3.049511) [0.0276]
D(merger (-3))	-7.531352 (-3.575902) [0.0178]	1.214378 (2.420470) [0.0284]
D(NPL)	7.873412 (8.292194) [0.0348]	-2.153824 (-2.997530) [0.0318]
D(investment to asset)	-5.678736 (-1.863977) [0.0313)\]	-4.219497 (-2.453970) [0.0327]
D(log assets)	3.222880 (5.775951) [0.0403]	4.098452 (3.245109) [0.0368]
D(GDP growth)	1.807830	1.483763

	(5.100500_ [0.0421]	(3.442798) [0.0473]
D(inflation)	-2.561931 (-8.573199) [0.0739]	-0.263383 (-9.903247) [0.0641]
D(Deposit interest rate)	-2.005420 (-5.8453648) [0.0109]	4.572519 (2.192418) [0.0290]
CointEq(-1)	-0.080139 (-2.986443) [0.0213]	-0.183706 (-2.953580) [0.0277]

* Dependent variable is operational risk
** Dependent variable is market risk
Source: Research Findings

8 Conclusion

Iran merged five military institutions in 2017. One of the object of the merger of those banks was risk management. A review of internal and external studies reveals, there are not any research about the effect of bank mergers on operational and market risk. Various studies examined the impact of bank mergers on the systemic risk of banks, and the results indicate an increase in systemic risk following bank mergers (Tanna & Yousef (2019), Amihud et al. (2002), Mishra et al. (2005), Bozos et al. (2013), and Casu et al. (2015)). This article examines the long- and short-term effects of the merger on operational risk and market risk, using the ARDL model. Results indicates, merger of banks increase operational risk and market risk in the short-term. Merger of banks increases operational risk and decreases market risk in the long term. These results are in line with Bozos et al. (2013), Casu (2015) and Tanna & Yousef (2019).

According to Sepah Bank's current human and software structure, the perpetuation of this structure in the future could increase operational risk, so the merger of banks cannot reduce it. Due to the fact that Sepah Bank is a state-owned bank, it does not have unrestricted access to the market; therefore, the merger of banks can increase market risk.

It is suggested the policymakers, before merging banks, pay attention to the business model of the bank, the state of market risk and operational risk, the type of ownership and the size of the bank. Before merging banks, problems such as market risk and operational risk should be controlled and managed. The effect of bank mergers on market and operational risk should be investigated according to macroeconomic conditions such as business cycles and inflation.

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Appendix

Table 11
Merger and operational risk (Dynamic Model)

Dependent Variable: V32
Method: ARDL
Date: 07/07/21 Time: 10:21
Sample (adjusted): 2000 2016
Included observations: 17 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): V14
Fixed regressors: V4 V1 V12 V26 V23 V25 C
Number of models evalulated: 20
Selected Model: ARDL (4, 4)

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
V32(-1)	0.626376	0.059190	10.58239	0.0600
V32(-2)	0.608894	0.166533	3.656301	0.1700
V32(-3)	0.491854	0.101688	4.836914	0.1298
V32(-4)	0.412449	0.093403	4.415820	0.1418
V14	-5.660535	5.030608	-11.25219	0.0564
V14(-1)	1.294487	3.848702	3.363438	0.1840
V14(-2)	1.873390	0.3665107	5.111420	0.1230
V14(-3)	2.680765	0.6691332	4.006324	0.1557
V14(-4)	7.605116	1.180107	6.444426	0.0980
V4	8.008034	2.374875	3.371982	0.1835
V1	-6.877292	6.665265	-1.031811	0.4900
V12	3.224118	8.688197	3.710917	0.1676
V26	1.873.256245361316	6.252762	2.986334	0.2057
V23	-2.705236	9.089940	-2.976077	0.2064
V25	-2.001871	2.589137	-7.731806	0.0819
C	8.507550	5.036140	1.689300	0.3403
R-squared	0.979666	Mean dependent var		31244.41
Adjusted R-squared	0.954660	S.D. dependent var		12388.43
S.E. of regression	905.2857	Akaike info criterion		15.50352
Sum squared resid	819542.2	Schwarz criterion		16.28772
Log likelihood	-115.7799	Hannan-Quinn criter.		15.58147
F-statistic	199.6846	Durbin-Watson stat		3.339959
Prob(F-statistic)	0.055482			

*Note: p-values and any subsequent tests do not account for model selection.

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Table 12
Merger and operational risk (Long Run)

Long Run Coefficients				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
V14	2.482255	6.988487	3.551921	0.1747
V4	2.550676	0.819429	3.112749	0.1979
V1	-2.190518	2.083981	-1.051122	0.4841
V12	1.026929	2.191428	4.686117	0.1338
V26	5.966595	2.078441	2.870708	0.2134
V23	-8.616571	2.525967	-3.411197	0.1815
V25	-6.376251	1.139968	-5.593359	0.1126
C	2.709779	1.748096	1.550131	0.3647

Table 13
Merger and operational risk (Co-integrating Form)

Co-integrating Form				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(V32(-1))	1.480735	0.059313	24.964940	0.0255
D(V32(-2))	0.884067	0.040716	21.712774	0.0293
D(V32(-3))	0.396566	0.029646	13.376715	0.0475
D(V14)	-5.696870	1.369218	-4.160675	0.0153
D(V14(-1))	-1.192255	0.425244	-2.803696	0.0227
D(V14(-2))	-1.005107	0.413778	-2.429100	0.0262
D(V14(-3))	-7.531353	2.106140	-3.575903	0.0178
D(V4)	7.873413	6.100775	1.292194	0.0348
D(V1)	-5.678737	3.046570	-1.863977	0.3135
D(V12)	3.222880	2.042907	1.577595	0.0403
D(V26)	1.807831	1.197199	1.510050	0.0421
D(V23)	-2.561932	0.298830	-8.573199	0.0739
D(V25)	-2.005421	0.343079	-5.845365	0.0109
CointEq(-1)	-0.080139	0.026846	-2.986443	0.0213

Cointeq = V32 - (2.48225517*V14 + 2.550676*V4 -2.190518*V1 + 1.02692870*V12 + 5.966595*V26 -8.61657*V23 -6.3762512*V25 + 2.70977912)

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Table 14
Merger and market risk (Dynamic Model)

Dependent Variable: V33
Method: ARDL
Date: 07/07/21 Time: 10:27
Sample (adjusted): 2000 2016
Included observations: 17 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): V14
Fixed regressors: V4 V1 V12 V26 V23 V25 C
Number of models evalulated: 20
Selected Model: ARDL (4, 4)

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
V33(-1)	4.032037	1.048297	3.846272	0.1619
V33(-2)	0.367931	0.179362	2.051329	0.2888
V33(-3)	2.446164	0.663244	3.688183	0.1686
V33(-4)	1.546672	0.811701	1.905470	0.3077
V14	1.298468	43.42209	2.990339	0.2054
V14(-1)	-6.186530	1.803608	-3.430086	0.1806
V14(-2)	-3.273892	2.158450	-1.516779	0.3711
V14(-3)	2.336077	1.483366	1.574849	0.3602
V14(-4)	-1.244748	0.250778	-4.963540	0.1266
V4	-2.229506	0.545987	-4.083439	0.1529
V1	-4.392892	1.477343	-2.973509	0.2065
V12	1.412161	0.450734	3.133023	0.1967
V26	1.589835	1.257318	1.264465	0.4260
V23	-0.276975	0.211494	-1.309609	0.4152
V25	4.166633	1.223900	3.404391	0.1819
C	-3.143049	94.28231	-3.333658	0.1855
R-squared	0.962806	Mean dependent var		5.705882
Adjusted R-squared	0.884904	S.D. dependent var		3.117786
S.E. of regression	1.057735	Akaike info criterion		1.999276
Sum squared resid	1.118802	Schwarz criterion		2.783476
Log likelihood	-0.993842	Hannan-Quinn criter.		2.077227
F-statistic	9.200945	Durbin-Watson stat		3.277193
Prob(F-statistic)	0.053794			

*Note: p-values and any subsequent tests do not account for model selection

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Table 15
Merger and market risk (Long Run)

Long Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
V14	-5.779298	4.182672	-1.381724	0.3988
V4	-0.353920	0.047786	-7.406367	0.0854
V1	-0.697344	0.185736	-3.754494	0.1657
V12	2.241718	0.483799	4.633570	0.1353
V26	0.252376	0.174837	1.443493	0.3857
V23	-0.043968	0.028830	-1.525058	0.3695
V25	6.614270	1.221113	5.416591	0.1162
C	-49.893951	9.247100	-5.395632	0.1167

Table 16
Merger and market risk (Co-integrating Form)

ARDL Cointegrating And Long Run Form

Dependent Variable: V33
Selected Model: ARDL(4, 4)
Date: 07/10/21 Time: 08:51
Sample: 1996 2018
Included observations: 17
Cointegrating Form

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(V33(-1))	1.261251	0.092077	13.697770	0.0464
D(V33(-2))	0.877810	0.072195	12.158903	0.0522
D(V33(-3))	-1.489268	0.098277	-15.153770	0.0419
D(V14)	1.262142	0.596363	2.116401	0.0301
D(V14(-1))	10.289496	4.571801	2.250644	0.0283
D(V14(-2))	9.923864	3.263158	3.049511	0.0276
D(V14(-3))	1.214379	0.541638	2.242047	0.0284
D(V4)	-2.153824	0.719064	-2.997530	0.0318
D(V1)	-4.219497	1.718367	-2.453970	0.0327
D(V12)	1.409845	0.432099	3.245109	0.0768
D(V26)	1.483763	0.430233	3.442498	0.0473
D(V23)	-0.263383	0.026596	-9.903247	0.0641
D(V25)	4.572519	2.086758	2.191242	0.0290
CointEq(-1)	-0.183706	0.061017	-2.953580	0.0277

Cointeq = V33 - (-5.7793*V14 -0.3539*V4 -0.6973*V1 + 2.2417*V12 + 0.2524*V26 - 0.0440*V23 + 6.6143*V25 -49.8940)

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