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RESEARCH PAPER

Systemic Risk Calculation in the Iranian Banking System, Employing the Conditional Value-at-Risk Approach (2009-2019)

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Abstract
Systemic risk is the collapse and crisis in the financial system that is caused by default or crisis in one or more firms. In this paper, the conditional value-at-risk ($CoVaR$) method is used as a measure for this kind of risk. This measure is going to be calculated for the five largest banks of the country including Mellat, Tejarat, Saderat, Parsian, and EN from June 17, 2009, to May 7, 2019, and the share of each bank in overall systemic risk is going to be identified. This paper is to investigate the effectiveness and participation of each of these banks in systemic risk. The results show that Parsian, Mellat, EN, Tejarat, and Saderat banks are the most involved in the systemic risk of the whole system, respectively. In addition, we try to calculate the effect of systemic risk of the entire banking system on each of these banks and the impact of each of these banks on the crisis in another bank. The results of this section indicate that in a crisis in the whole system, Mellat bank is the most stable bank, and accepts less impact of the crisis than other banks. By contrast, Parsian and Tejarat banks are the most affected by the crisis in the banking network.
Keywords: Banking System, Conditional Value-at-Risk ($COVaR$), Systemic Importance, Systemic Risk, Value-at-Risk (VaR).
JEL Classification: C21, G01, G21, G32.

Introduction

Systemic risk in the financial system is a risk that is caused by the failure of an institution to fulfill its inherent tasks, which may cause other institutions to fail in their duties. Systemic risk in the financial system is defined as the risk of the presence of crisis in an institution or the failure of an institution in fulfillment of its inherent duties, which propagates to other institutions, dooming them to failure in fulfilling their duties as well.

This chain of reactions can lead to more significant financial problems on a larger scale and the collapse of the financial system.

This chain of responses can lead to larger financial problems at a wider level. The expansion of crisis in an institution to other institutions simply is due to the financial connections between them, such as interbank facilities, payment systems, etc. This has been the case in recent years during the financial crisis when the crisis can quickly expand through the financial system, and challenge the sustainability of the financial system. A systemic crisis that disturbs the sustainability of the financial system can have serious consequences for the economy, and create huge costs for the entire economy and society. Reverse and adverse effects in the real sector of the economy due to systemic problems are visible in the increased disturbance of the payment system and credit trends, as well as the depreciation of assets. Two related assumptions

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underlie the definition of systemic risk. First, economic shocks can become systemic due to the negative externalities associated with disrupting the financial system. Second, systemic events are likely to have unintended effects, such as significant reductions in production and employment, due to a lack of accountability and appropriate policies. In this definition, financial turmoil that is unlikely and does not cause significant disruption to real economic activity is not a dangerous systemic event. Usually, the banking system is the starting point for systemic risk analysis in a country. It is due to the critical role of banks in the financial intermediation, maturity conversion, as well as in the operation of granting facilities and creating leverage. Besides, historical evidence shows that a fragile banking system significantly affects the economic growth of countries. Examining the situation of the country's banks in recent years and based on the method of events and the money market pressure index (which are the methods used in empirical studies to identify banking crises) confirms the presence of the banking crisis in the country. Incidents such as the merger of some banks and financial institutions, the restructured banking sector, some government's support for the banking system, the sharp increase in non-performing loans, increased liquidity risk in the banking sector, the sudden withdrawal of deposits, etc. are among the facts that confirm the presence of a banking crisis in the country.

Before 2007, the Basel II regulatory framework was developed for risk management based on individual characteristics, and systemic evaluation did not have a role. Basel II uses capital as a buffer against unpredictable losses, and internal risk management models are designed based on value-at-risk. These models generally do not consider the feedback of an institution on losses incurred by other institutions (Borri et al., 2012).

The 2008 financial crisis changed the perception of risk in financial markets, after which the emphasis on systemic risk analysis has increased, and the systemic risk indicators that can be used by central banks and others as a tool to monitor this risk have been expanded. The ability to quantify and measure the amount of risk that puts the financial system in vulnerability is worthwhile for central banks. The purpose of this paper is to estimate and analyze the risk dependencies among banks as well as the banking system by applying VaR and $CoVaR$ methods. The outcome reveals and ranks both the most affecting and affected banks in terms of systemic risk in the banking system. The paper will show how the banks affect each other mutually in terms of risk. To achieve these goals, the $CoVaR$ method, developed by Brunnermeier and Adrian (2011), which is a measure to calculate systemic risk, is used.

$CoVaR$ measures the amount of financial institutions' assistance to systemic risk as well as the risk of other financial institutions. $CoVaR$ denotes the value-at-risk of a financial institution conditional on the existence and establishment of a specific scenario. Here, the $CoVaR$ measure is used to estimate the systemic risk that can disrupt the sustainability of the financial system in the banking sector of the country. The contribution of each bank in overall systemic risk, namely $\Delta CoVaR$, refers to the difference between $CoVaR$ if institution I is in crisis and $CoVaR$ if the same institution is in its normal state. Systemic risk results obtained from $\Delta CoVaR$ measure differ from those of VaR measure. Here, we have calculated the $\Delta CoVaR$ value in three different states. At the first state, we have obtained the contribution of individual banks in the overall systemic risk of the banking system. The second state discusses the mutual impact of banks and, finally, at the third state, we assess how much each bank gets affected by the crisis in the banking system.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the subject matter, and Section 3 provides the theoretical foundations. In Section 4, the model and the data are described, and in Section 5, the model and the results are estimated. Finally, Section 6 concludes the paper.

Literature Review and Theoretical Foundations

An Overview of the History of Research on Systemic Risk

Systemic risk studies have been conducted in two ways: one is to identify and introduce systemic risk measures that researchers are interested in understanding how different factors or institutions are related in terms of risk, and the second is to identify the effective factors on systemic risk. These researchers have tried to identify important factors influencing systemic risk, and improve the economic policy accordingly. Following the presentation of the methodology proposed by Adrian and Brunnermeier (2011), several studies have been conducted on the calculation of systemic risk using this methodology.

These studies have investigated the systemic risk, and the tools to study the spread of risk, and the number, the contribution, and the effectiveness of any institutions in systemic risk.

Roengpitya and Rungchaoenkitkul (2010) used the $CoVaR$ to identify the quantity of risk and financial communication between the six main commercial banks of Thailand from 1996Q2 to 2009Q1. They found that larger banks had a greater stake in the systemic risk.

Lopez-Espinoza et al. (2012), identifying the main systemic risk factors in a set of international banks with $CoVaR$ approach, found that there was no evidence that bigger banks were increasing systemic risk in the group of large international banks. They confirmed that the short-run financing of wholesale was a major driver at the beginning of systemic risk. Their results support the Basel Committee's plan on maintaining a sustainable financing ratio and the imposition of fines in case of excessive pressure on liquidity risk.

Borri et al. (2012) studied the participation rate of 223 European banks in the systemic risk over the period 1999–2010. They analyzed the spread of systemic risk from European banks to the rest of the world as well as from other banks to the European banks. They found $\Delta CoVaR$ as an effective and applicable policy tool, as it could identify which characteristics of the banks may have a greater contribution to systemic risk. Their results showed that 1. $\Delta CoVaR$ was persistent that is risky banks tend to remain risky. 2. Recent policy discussions emphasized the dangers imposed on the system by large banks and the need to control their size. Therefore, size is one of the predictors of the degree of participation and effectiveness in systemic risk, but other variables are involved in this, and size is just one of the factors, not the only important factor. 3. They realized that even with the control of the banks' size by each country, they continued to affect the systemic risks. Therefore, they found that the design of the regulations governing the bank size could not by itself eliminate the systemic risk. 4. The available variables in the financial statements of banks are weaker market-based variables to predict bank participation in systemic risk.

Girardi and Ergün (2013) adjusted the $CoVaR$ method of Adrian and Brunnermeier (2011) by modifying the definition of the financial crisis from the institution that was exactly at VaR to an institution that was at the maximum level of VaR. They reviewed the participation of four groups of financial activists in a systemic risk over the period from 2000:6 to 2008:2. According to their study, depositary institutions, brokers, insurance companies, and non-depositary institutions had the most effects on systemic risk. In addition, they calculated Δ for the four groups and observed that systemic risk had risen increasingly in all four groups before the crisis began.

Bernardi et al. (2014) through multivariate student-t Markov switching and multiple $CoVaR$ models analyzed the interdependence of tail risk between US banks, the financial services sector, and the insurance sector for the period 1992 to 2002. Their study aimed at assessing the contribution of different financial sectors to overall risk, and their degree of interdependence. Results confirmed that in the US financial market during the reviewed period, the banking sector was the main source of risk in other sectors, after which the financial services sector, and then the insurance sector had the greatest impact on the overall risk.

Guathier et al. (2012) acquired an estimate of how much the Canadian banking system was exposed to risk, then used $CoVaR$ model as a criterion for allocating risk and considering the role that each institution had in systemic risk, compiled a set of macro-prudential policies related to capital requirements.

Segoviano and Goodhart (2009) used Credit Default Swap data (CDS) and expanded the bank's sustainability assessment, which evaluated the participation of banks in systemic risk in a multivariable framework.

Huang et al. (2009) submitted a representation for the systemic risk measured by the insurance price in a situation of urgency and a systemic financial constraint. In the proposed model, it is determined the conditions of urgency and financial bottlenecks based on pre-metric criteria, the probability of banks default, and predictions of stock return correlation.

Zhou (2010) assessed the systemic importance of financial institutions in the framework of multivariate extreme value theory (EVT) and proposed two measures for the systemic risk: 1. The systemic impact index (SII) measures the size of systemic effect if a bank becomes bankrupt, and 2. The vulnerability index (VI) that calculates the impact on a particular bank, at the time that the rest of the system is in a financial emergency.

Brownlees and Engle (2012) developed the SRISK index, which was the deficit of the expected capital of a firm, conditional on a major downgrade in the market as a systemic risk substitute. The SRISK index is a function of the leverage, size, and expected capital shortfall of an institution.

Kleinow and Moreira's (2016) paper evaluates the systemic risk in the euro area using a credit default swap (CDS) of the European banks. In addition, they tried to explain why some banks expected to affect the systemic risk in the region negatively.

Brownlees and Engle (2017), to provide other modern econometric approaches to systemic risk measurement, presented the marginal expected shortfall (MES) approach.

Liu (2017) proposed the use of a switching regimen model to illustrate non-linearity in the sequence of contributions of each institution in systemic risk.

Rastegar and Karimi (2016) calculated systemic risk in the banking sector, using $\Delta CoVaR$ and the dynamic conditional correlation (DCC) model. They analyzed its relevance to the bank's main characteristics, including value-at-risk, leverage, and capital ratios with the help of regression of panel data from 2010 to the beginning of 2014. However, in terms of market value, the banking sector involved only 9% of the total market value, but the results showed that the systemic risk of the whole market was highly related to the banking sector, which was around 71%. In addition, the systemic risk rating of the studied banks in the study period has changed dramatically.

Theoretical Framework

Systemic Risk

Systemic risk in financial literature means the possibility of a collapse in a financial system. This risk can lead to instability or turmoil in financial markets. Another important issue in the systemic risk debate is risk contagion. That is the likelihood of expansion of a major economic change in one country to other countries, or a crisis at an institution to other institutions. The banking crises of preceding decades, and at the top of them, the financial crisis of 2007–2012, has led to the consideration of systemic risk issues in financial markets to be addressed by macroeconomic policymakers.

Group of Ten refers to the systemic risk as a risk in which an event or incident causes a loss in economic value or level of assurance in economic activity, and extends uncertainty in the economy. In this case, a significant part of the financial system is quite capable of reversing and opposing influence in the real sector of the economy. Systemic risk events can be sudden and unpredictable (Group of Ten, 2001).

Systemic risk can be described with three factors: 1. It affects a significant part of the financial system. 2. It involves external implications. 3. Preventing the expansion and ultimately management of this type of risk requires the intervention of the authorities.

Quantile Regression

Quantile regression developed by Koenker and Basset (1978) is an effective method for estimating $CoVaR$. Quantile regression provides the relationship between an independent variable (or a set of independent variables) and specific quantiles of the dependent variable. In ordinary least square (OLS) regression, the coefficients estimate the change in the mean of the dependent variable by a unit of change in the independent variable, assuming that other independent variables are constant. However, the coefficients of a quantile regression estimate the change in a specified quantile of the dependent variable, which is derived from a unit of change in the independent variable. This compares how different quantiles of the dependent variable are influenced by the independent variable. This allows comparing how the different quantiles of dependent variables can be influenced by the independent variable. Given that at the time of estimation of $CoVaR$ focus is on the lower quintile distribution, this type of regression is appropriate for this study.

Compared to the OLS method, one of the advantages of quantile regression is that if there is any outlying data, estimates of this method are much more accurate than that of ordinary least squares.

In addition, compared to the conventional regression methods, quantile regression can determine the entire conditional distribution of the dependent variable and, if the distribution of error term is incorrect, it obtains more precise estimates. Quantile regression models are not only to determine the heterogeneous effects of variables in different quantile of independent variables, they are used in the event of a violation of the normality assumption, the existence of outlying data, and the existence of long sequences distributions.

These advantages for quantile regression make it attractive and usable for a variety of data including independent data, time-to-event data, and longitudinal data.

Quantile $\tau \in [0,1]$ of F distribution with the distribution function $F(y) = p(Y \leq Y)$ is defined as follows:

$\mathrm{F}^{-1}(\tau) = \inf\{y: \mathrm{F}(y) \geq \tau\}$

Now if the loss function is defined as $\rho_\tau(y) = y(\tau - I(y<0))$, then τ quantile can be quantified by estimate y that minimizes the expected loss $(Y-y)$ through the following equation:

$$\mathrm{E}\big(\rho_\tau(\mathrm{Y}-\hat{\mathrm{y}})\big) = \int \rho_\tau(\mathrm{y}-\hat{\mathrm{y}}) = (\tau-1)\int_{-\infty}^{\hat{\mathrm{y}}} (\mathrm{y}-\hat{\mathrm{y}})\mathrm{dF}(\mathrm{y}) + \tau\int_{\hat{\mathrm{y}}}^{\infty} (\mathrm{y}-\hat{\mathrm{y}})\mathrm{dF}(\mathrm{y})$$

We use the derivative, and equal it to zero to get:

$$0 = (\tau-1)\int_{-\infty}^{\hat{\mathrm{y}}} \mathrm{dF}(\mathrm{y}) + \tau\int_{\hat{\mathrm{y}}}^{\infty} \mathrm{dF}(\mathrm{y}) = \mathrm{F}(\hat{\mathrm{y}}) - \tau$$

It obtains that $\mathrm{F}(\hat{\mathrm{y}}) = \tau$, and from there, finally we have $\hat{\mathrm{y}} = \mathrm{F}^{-1}(\tau)$. According to the above-mentioned definition, $\hat{\mathrm{y}}$ is the τ^{th} quantile of the F distribution. If the distribution of F is a discrete distribution, the τ quantile based on the above equations is calculated by minimizing the following equation:

$$E\big(\rho_\tau(Y-\hat{y})\big) \approx \frac{1}{n}\sum_{i=1}^{n}\rho_\tau(y_i-\hat{y})$$

If the conditional quantile function of Y distribution with the data is considered to be the distribution of X for a given quantile as defined below $Q_y(\tau|x) = x^\tau\beta_\tau$, by derivation, the following equation can be minimized:

$\frac{1}{n}\sum_{i=1}^{n}\rho_\tau(y_i - x^\tau\beta_\tau)$.

The regression coefficients $\beta\tau$ represent the change in $Q_y(\tau|x)$ due to a unit of change in one of the vector components of x^τ.

Value-at-Risk

Value-at-risk is a well-known widely used measure for risk measurement by financial institutions. Value-at-Risk measures the potential losses in the value of an asset or a risky portfolio over a specified period with a specific confidence level. This criterion calculates the amount of capital that may be lost in a time interval like a day, assuming the probability function is determined and market conditions are normal. With a distinct portfolio and a determined time horizon and probability p, the value-at-risk can be defined as a maximum loss in that time frame. It should be emphasized that in this definition, all worse possible outcomes (events with higher value losses whose combined probability is greater than p) are not included in the definition.

For example, if a one-day value-at-risk with a confidence level of 95% of a portfolio of shares equals 100 million Iranian Rials, it is 95% likely that the maximum loss of this portfolio will be 100 million Iranian Rials per day, and with the probability of 5%, some events cost more than 100 million Iranian Rials per day. The value-at-risk is defined by the following equation:

$$p\big(x_t \le \mathrm{VaR}(t,k,q)\big) = 1 - q \tag{1}$$

In this regard, x_t is the yield of the basket of assets in the period t, and k is the period for which the value-at-risk is computed, and q is the probability level. According to the definition, the value-at-risk is generally a negative number and represents the q^{th} quantile of the yield. The biggest advantage of value-at-risk is that it summarizes the negative dimension of the risk of an institution as an intelligible number. Value-at-risk also has some limitations that should be known when using it. One of these limitations is that although the value-at-risk estimates the possible losses for one specific quantile, it does not specify the extent to which loss can be considered for the lower quantile. Another limitation is that value-at-risk is not necessarily accumulative. That is, the value-at-risk of a portfolio that is a combination of two other portfolios cannot necessarily be achieved by summing up the value-at-risk of the two primary portfolios.

Several methods have been proposed for calculating value-at-risk, which can be categorized into four general categories: parametric methods (econometric models), nonparametric methods (historical simulation), quasi-parametric methods, and Monte Carlo simulation method.

If x represents the returns of the portfolio, and the returns are distributed by F, and the confidence level is equal to (1-q), then (x_t) can be defined as: $\mathrm{VaR}_q(x_t) = \inf\{x_t: F(x_t) \ge q\}$

By this definition, the value-at-risk is essentially the q^{th} quantile of the F distribution.

Model

Conditional Value-at-Risk (COVaR) Model

Given the aforementioned definition of value-at-risk, the $CoVaR$ model can now be defined. The $CoVaR$ expression stands for $CoVaR$. Value-at-risk of a financial system (or a special bank, portfolio of assets, etc.) is defined as value-at-risk of a financial system, conditional to several scenarios in a specific bank or a set of banks. In the theoretical literature, there are 3 methods for a calculation of the $CoVaR$ that are:

1. Quantile regression (Adrian and Brunnermeier, 2008; Lopez et al., 2012; Borri et al., 2014);
2. Multivariate GARCH Model (Girardi and Ergün, 2013);
3. Copula Method (Roboredo and Ugolini, 2015).

In the estimation based on the multivariate GARCH model, in the first step, the value-at-risk of each institution is estimated, then it is used the bivariate dynamic conditional correlation (DCC) model for estimating the joint distribution of joint returns of the financial system and each financial institution. The $CoVaR$ is obtained by numerical calculations of the dual integral. In the Copula-based approach, the joint distribution of each pair of returns is expressed by Copula. This approach is flexible modeling of marginal distributions and dependency structures. The problem with the GARCH and Copula methods is that these two models are very complex for users and legislators, while quantile regression is comparatively simpler than the two methods mentioned.

In this paper, the quantile regression method introduced by Adrian and Brunnermeier is used to calculate the $CoVaR$. Suppose that X^{j} is the return on the assets of a financial system (or bank j), and X^i is the return on the assets of bank i. In Equation 1, we showed the definition of value-at-risk, now in the equation below, the conditional event is added to the definition of value-at-risk. Equation 2 is the $CoVaR$ of a financial system (or bank j) provided that the level of value-at-risk of the bank i is q percent (Bank i is at the level q of value-at-risk). q is the given quantile for distribution of X^{i}:

$$\mathrm{P}\left(\mathrm{X}^{\mathrm{j}} \leq \mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j|i}} \middle| \mathrm{X}^{\mathrm{i}} = \mathrm{VaR}_{\mathrm{q}}^{\mathrm{i}}\right) = \mathrm{q} \tag{2}$$

In other words, the probability that the returns of the system (X^{j}) be less than $\mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j|i}}$ is equal to q when at a specific time interval the return on the bank i will be at the value-at-risk of q (It can be said that with a probability of q, return on assets of the system (X^{j}) is less than $\mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j|i}}$ when at a given time interval, the bank i’s yield is at the value-at-risk of q).

To measure the impact of bank i on the value-at-risk of a financial system (or bank j) in a stressful period in bank i, Adrian and Brunnermeier used the difference between value-at-risk of the system on a condition that bank i be at its value-at-risk level, and the value-at-risk of the system on condition that bank i be at its average level:

$$\begin{aligned}&\Delta\mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j|i}} = \\ &(\text{CoVaR of institution j conditional on institution i being at its VaR level}) - \\ &(\text{CoVaR of institution j conditional on institution i being at its median level})\end{aligned} \tag{3}$$

$$\Delta\mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j|i}} = \mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j|X^i=VaR_q^i}} - \mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{j|X^i=Median^i}} \tag{4}$$

Estimation

Quantile regression is an effective method for estimating the relationship between the $CoVaR$ of a financial system and each bank, as well as every pair, is in the banks. When we compute the value-at-risk or the $CoVaR$, we consider the least quantile of the distribution. So, it is easier to use quantile regression rather than OLS regression. Using the time series of the return on assets of each bank, the X^i and X^{system} distributions are estimated. Adrian and Brunnermeier defined the system's return on assets based on the weighted sum of the return on assets of each bank that has been proportioned based on the past market value of assets. Using the time series, the following quantile regression can be conducted:

$$X^j = \alpha_q^i + \beta_q^i X^i + \varepsilon \tag{5}$$

This equation shows regression X^j (j can be the system or any bank $j \neq i$) on X^i for each institution i. The quantile regression coefficient β_q^i estimates changes to a specified q quantile of X^jcreated by a unit change in X^i. In other words:

$$\hat{X}_q^{j,i} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \tag{6}$$

Using the definition and Equations 4 and 6, we have:

$$\mathrm{CoVaR}_q^{j|X^i=\mathrm{VaR}_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i \mathrm{VaR}_q^i \tag{7}$$

$$\mathrm{CoVaR}_q^{j|X^i=\mathrm{Median}^i} = \mathrm{CoVaR}_q^{j|X^i=\mathrm{VaR}_{50}^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i \mathrm{VaR}_{50}^i \tag{8}$$

Finally, the impact of bank i on the value-at-risk of bank j (or any financial system if $j = system$) equals to:

$$\Delta\mathrm{CoVaR}_q^{j|i} = \hat{\beta}_q^i \left(\mathrm{VaR}_q^i - \mathrm{VaR}_{50}^i\right) \tag{9}$$

Estimation of the Model and the Results

Data

To make estimates and to illustrate the interdependence of risk between several existing market organizations that may be at the same time in a bottleneck, this paper studies the banking industry of Iran, and calculate the extent and degree of dependence of the banks on each other in the existing systemic risk, the weekly returns of Mellat, Tejarat, Saderat, Pasian, and EN banks (which are the listed companies in the Tehran Stock Exchange) are used that contains 517 data for each time series in the period from June 17, 2009, to May 7, 2019. The selected banks are from large state and private banks, accounting for a total of 30.8% of the total assets of the Iranian banking system.

The required information was obtained from the Tehran Stock Exchange and the Central Bank of the Islamic Republic of Iran.

Estimated Results

Not only is the legislature seeking to be aware of the possibility of bank failure, but they are also paying attention to the adverse effects of a crisis in a financial institution on the entire financial system. In other words, the legislator considers the negative external consequences of a crisis in a financial institution over other institutions and the entire financial system. To understand this, we first calculate the VaR and then obtain the $\Delta\ CoVaR$ for each bank. There are various methods to estimate the $CoVaR$. Adrian and Brunnermeier (2011) proposed quantile regression for estimating VaR and $\Delta CoVaR$ variables. They used a set of state variables as regressors to estimate q quantile parameters for fitting the estimated $CoVaR$ and VaR. The great advantage of this method is that they did not consider specific distribution on random variables and to obtain VaR and $CoVaR$ variables. In this paper, a different econometric framework was used to illustrate the above methodology. To avoid the process of what state variables should be selected, we work directly with individual returns[1].

As explained, quantile regression shows how each bank is linked to specific quantiles of the system growth rate, and from the results, the $CoVaR$ and $\Delta CoVaR$ can be estimated. Before going deep down on the issue, the data used in the article are reviewed and a summary of descriptive statistics is presented in Table (1).

Table 1. Summary of Descriptive Data Statistics

SYS	SAD	TEJ	MEL	PARS	EN	
-0.0021468	0.00029269	0.00045288	0.0015184	-0.0258198	0.0011573	**average**
0.12756	0.27303	0.27635	0.20634	0.20729	0.57530	**max**
-1.3000	-0.60392	-0.79581	-0.39596	-0.33352	-0.29084	**min**
0.077694	0.050280	0.063667	0.046733	0.041871	0.052714	**Standard deviation**
-12.230	-4.6111	-5.3744	-1.9174	-0.42619	2.1888	**skew**
178.64	58.863	65.492	20.481	10.860	32.963	kurt
31756	361.50	698.02	458.79	578.06	923.70	**normality**
0.0	0.0	0.0	0.0	0.0	0.0	**p_value**

Source: Research finding.

Mellat and Parsian banks with average returns of 0.0015184 and -0.0258198 during the period under review have the highest and lowest returns, respectively. Standard deviation indicates risk or fluctuation of data. Parsian Bank with 0.041871 has the lowest fluctuation and Tejarat Bank with 0.063667 has the highest fluctuation among the data. The skewness of all data except the EN bank is negative, and this shows asymmetry in the data. The kurtosis variable indicates the fat tail of the distribution and the distribution of the data around the mean. The kurtosis values of all data are greater than 3 and indicate that the data distribution is not normal. According to the p-value values presented in the table above, the null hypothesis that it is normal for all data is rejected.

Mellat and Parsian banks with average returns of 0.0015184 and -0.0258198 during the period under review have the highest and lowest returns, respectively. Parsian bank with the standard deviation of 0,041871 and the Tejarat with that of 0,063667 has the lowest and highest data fluctuations, respectively, within the banking system. The skewness of data for all banks, except for EN bank, is negative which an indication of data asymmetry.

The kurtosis variable reveals the nature of the data distribution in the case of fat tail distribution and also dispersion around the mean. The Kurtosis values for the data of all banks are greater than 3, implying that that data distribution is not normal. Considering P-values presented in table (1), the null hypothesis of normality of all data is rejected.

Charts 1–5 describe changes in regression coefficients with quantile when the system is regressed on each bank. In these charts, the blue lines represent the coefficients of β and α, and the red lines indicate a 95% confidence interval. Quantile regression shows how the coefficients of independent variables change over different quantiles, and the way of interpreting the

1. By choosing different state variables, quantile estimation results may change

coefficients in this model is the same as OLS regression.

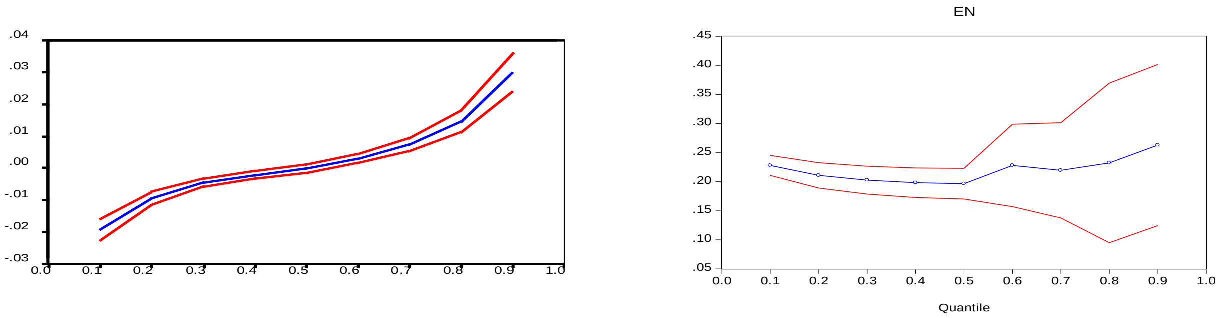

Figure 1. The Quantile Regression Parameter α and β as a Function of the Regression Quantile q: EN Bank

Source: Research finding.

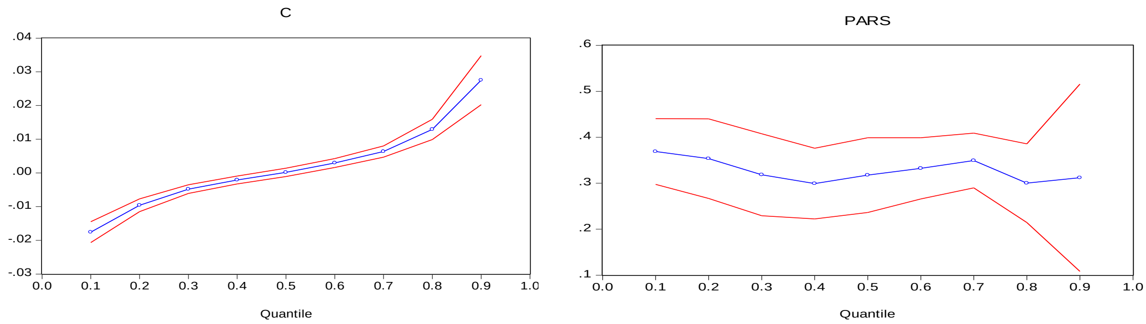

Figure 2. The Quantile Regression Parameter α and β as a Function of the Regression Quantile q: PAR Bank

Source: Research finding.

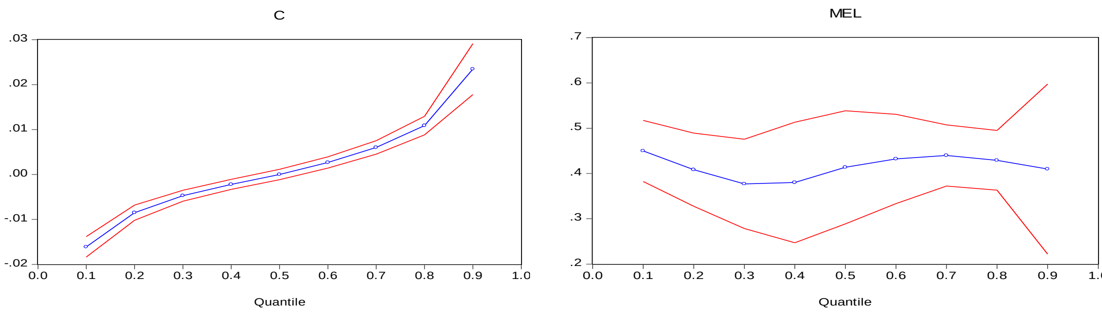

Figure 3. The Quantile Regression Parameter α and β as a Function of the Regression Quantile q: MEL Bank

Source: Research finding.

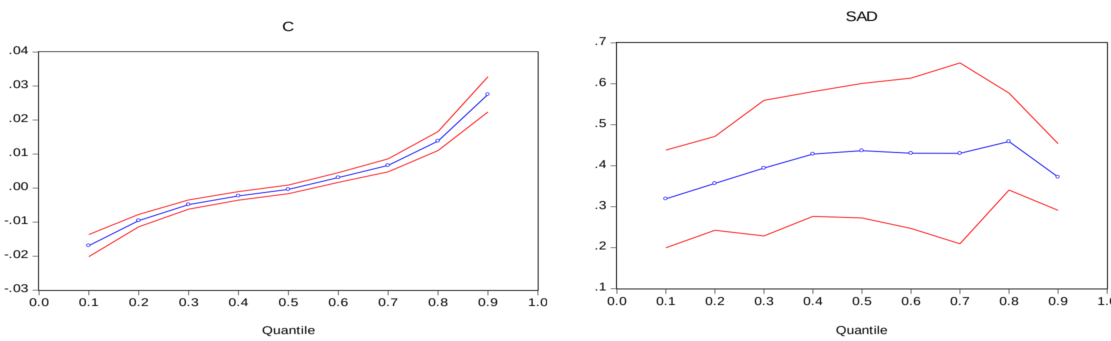

Figure 4. The Quantile Regression Parameter α and β as a Function of the Regression Quantile q: SAD Bank

Source: Research finding.

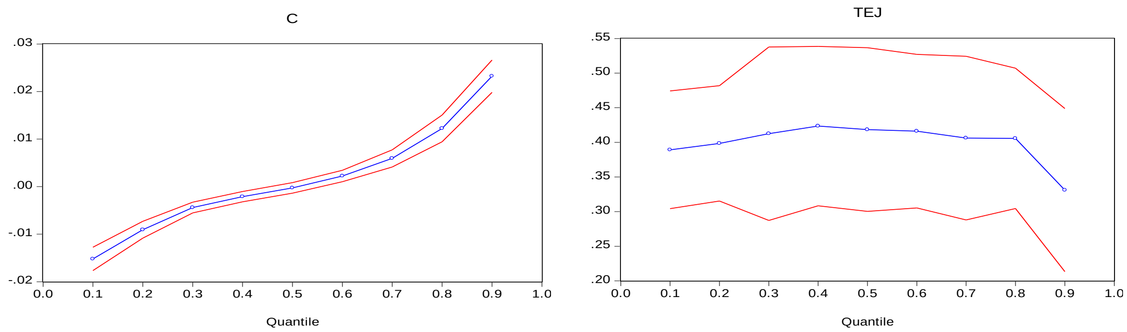

Figure 5. The Quantile Regression Parameter α and β as a Function of the Regression Quantile q: TEJ Bank
Source: Research finding.

The diagrams above show the relationship between different quantiles and the estimated values for each bank. The estimated α and β parameters of the quantile regression for each of the banks under study in quantile levels 1%, 5%, and 50% are also presented in Table 2.

Table 2. The Quantile Regression Parameters When Regressing the System on Bank i

SAD	TEJ	MEL	PARS	EN		
-0.0244	-0.0231	-0.0219	-0.0263	-0.0294	**α**	**5% quantile**
-0.02843 -0.02056	-0.02714 -0.01917	-0.02520 -0.01865	-0.03159 -0.02089	-0.03603 -0.02272	**Confidence interval**	
0.3032	0.3080	0.4394	0.3676	0.2456	**β**	
0.27313 0.33332	0.21628 0.39905	0.39564 0.48228	0.29600 0.43951	0.22460 0.26650	**Confidence interval**	
-0.0479	-0.0436	-0.0494	-0.0692	-0.0621	**α**	**1% quantile**
-0.06462 -0.03126	-0.05204 -0.03513	-0.06311 -0.03585	-0.10388 -0.03458	-0.08333 -0.04079	**Confidence interval**	
0.3890	0.2685	0.5922	0.4397	0.2996	**β**	
0.31416 0.46408	0.22159 0.31546	0.48441 0.70049	0.28306 0.59635	0.26142 0.33774	**Confidence interval**	
-0.0002	-0.0004	0.0001	0.0002	-0.0001	**α**	**50% quantile**
-0.00134 0.00086	-0.00164 0.00090	-0.00111 0.00121	-0.00106 0.00141	-0.00139 0.00124	**Confidence interval**	
0419499	0.4374	0.4142	0.3179	0.1960	**β**	
0.30260 0.53640	0.27303 0.60180	0.28982 0.53868	0.23652 0.39928	0.16976 0.22228	**Confidence interval**	

Source: Research finding.

In Table 3, value-at-risk for each of the banks as well as the entire system (includes 5 selected banks) is estimated. Value-at-risk is calculated using the historical data method at the level of 50%, 5%, and 1 % for each bank as well as the entire system.

Table 3. Value-at-risk for each of the Banks and the Whole System at Different Confidence Levels

SYSTEM	TEJ	SAD	MEL	PAR	EN	
-3.13%	-5.81%	-5.32%	-5.05%	-6.39%	-5.57%	**VaR**(5%)
-9.69%	-18.15%	-12.00%	-14.19%	-11.72%	-15.08%	**VaR**(1%)
-0.07%	0%	0%	0%	0%	0%	**VaR**(50%)

Source: Research finding.

According to the results of the above table, at the quantile level of 5%, Parsian Bank, with 6.39% has the highest value-at-risk among the selected banks. While Mellat Bank, with 5.05%, has the lowest value-at-risk at the quantile level of 5%. It is observed that with the change of the selected quantile level, the order of the selected banks' changes based on the value-at-risk. For example, at the quantile level of 1%, EN Bank has the highest value-at-risk. Besides, the calculated VaR values for the whole system are significantly less than VaR values for individual banks in all quantiles examined. Using the estimated parameters and Equations 7–9, $CoVaR$ and $\Delta CoVaR$ of the entire system have been calculated on condition that each bank is in crisis. The results have been reported at various levels of confidence.

Table 4. COVaR and ΔCOVaR of the System Conditional on Bank i

SAD	TEJ	MEL	PAR	EN	
-4.05	-4.10	-4.41	-4.98	-4.31	$\mathbf{COVaR}(\mathbf{5}\%)$
-9.46	-9.23	-13.35	-12.07	-6.66	$\mathbf{COVaR}(\mathbf{1}\%)$
0.0	0.0	0.0	0.0	0.0	$\mathbf{COVaR}(\mathbf{50}\%)$
-4.05	-4.10	-4.41	-4.98	-4.31	$\Delta\mathbf{COVaR}(\mathbf{5}\%)$
-9.46	-9.23	-13.35	-12.07	-6.66	$\Delta\mathbf{COVaR}(\mathbf{1}\%)$

Source: Research finding.

$\mathrm{CoVaR}^{\mathrm{system/bank\ i}}$estimates value-at-risk of the entire system at the mentioned confidence level on the condition that bank i is in a crisis. For example, $CoVaR$ (5%) = –4.31% implies that value-at-risk of 5% of system is –4.31% if the EN Bank is at its 5% value-at-risk level.

$\Delta CoVaR$ (5%) indicates that how much each selected bank increases the value-at-risk of the whole system when the level of confidence changes from 50% to 5%. For example, $\Delta\mathrm{CoVaR}(5\%) = -4.31\%$ denotes that if the value-at-risk of the EN Bank changes from 50% to 5%, this would increase (5%) of the entire system by 4.31%. According to Table 4, Parsian, Mellat, EN, Tejarat, and Saderat banks are most contributing to the systemic risk of the entire banking system, respectively. In other words, for policymakers and regulators, the crisis in Parsian, Mellat, Eghtesad-e-Novin, Tejarat, and Saderat banks is respectively of the utmost importance, because the amount of risk transfer from each of these banks to the entire system is listed in order of priority.

The estimation results of Conditional Value-at-Risk (CoVaR) average at the time of critical conditions (quantile 0.01) during the observation period showed that Mellat Bank has the highest CoVaR value, which amounted to -13.35%, while the lowest CoVaR on EN Bank, ie by -6.66%. The value of the conditional VaR system, amounting to -13.35% when Mellat Bank is in a state of distress. That is the state of distress in Mellat Bank will give effect to the system that impact the system will suffer a loss of 13.35%. The value of the conditional VaR system, amounting to -6.66% when EN Bank is in a state of distress. That is the state of distress in EN Bank would give effect to the system that impact the system will suffer a loss of 6.66%.

Marginal CoVaR (ΔCoVaR) represents the difference CoVaR at the time of distress and CoVaR condition when the condition of the median. The estimation results of marginal Conditional Value-at-Risk (ΔCoVaR) average over the study period showed that Pars Bank has the highest ΔCoVaR value, which amounted to -4.98%, while the lowest ΔCoVaR at SAD Bank, amounting to -4.05%. Value marginal CoVaR (ΔCoVaR) PARS Bank is -4.98% which means that PARS Bank contributes 4.98% of systemic risk in the system when migrating from the median VaR to the extreme, in this case VaR 5%. The value of the marginal CoVaR (ΔCoVaR) SAD Bank amounted to -4.05% which means that SAD Bank contributes 4.05% of systemic risk in the system when migrating from the median VaR to the extreme, in this case, VaR 5%. It is observed that by changing the level of the quantile understudy, not only the ΔCoVaR values but also the order of the banks in terms of their systemic importance, change.

Since any adverse shock to a bank or any other financial institution can spread quickly to other financial institutions or economic sectors, thereby declining production and employment, policymakers should take prompt reactions to prevent shocks to spread.

Based on the results obtained, and considering that the occurrence of negative shock in Parsian Bank has more severe negative effects on the entire banking system, policymakers should put Parsian bank high on the agenda for problem-solving.

The estimation of the relationship between each bank and the estimation of the impact of each bank on the quantile of the other banks are also examined in this paper. The results are reported in Table 5.

Table 5. The Quantile Regression Parameters When Regressing Each Bank j on Each Bank i

Independent variable							
TEJ	**SAD**	**MEL**	**PARS**	**EN**			
-0.0538	-0.0565	-0.0596	-0.0596	-	**α**	**EN**	**Dependent variable**
-0.078277 -0.029323	-0.067655 -0.045312	-0.081414 -0.037750	-0.082559 -0.036674	-	**Confidence interval**		
0.1813	0.3653	0.3956	0.4887	-	**β**		
0.048436 0.314082	0.343821 0.386819	0.193951 0.597194	-0.049536 1.026866	-	**Confidence interval**		
-0.0596	-0.0626	-0.0607	-	-0.0638	**α**	**PARS**	
-0.070318 -0.048802	-0.074404 -0.050772	-0.071474 -0.049915	-	-0.075962 -0.051581	**Confidence interval**		
0.1896	0.2457	0.3209	-	0.2322	**β**		
0.014981 0.358806	0.184140 0.307344	0.208825 0.432936	-	0.095351 0.369045	**Confidence interval**		
-0.0428	-0.0498	-	-0.0500	-0.0520	**α**	**MEL**	
-0.050830 -0.034695	-0.062726 -0.036937	-	-0.060406 -0.039521	-0.061671 -0.042230	**Confidence interval**		
0.4163	0.3239	-	0.2294	0.3093	**β**		
0.223518 0.609018	0.259323 0.388525	-	0.155640 0.303155	0.285899 0.332736	**Confidence interval**		
-0.0449	-	-0.0468	-0.0497	-0.0557	**α**	**SAD**	
-0.050703 -0.039185	-	-0.054606 -0.038960	-0.059229 -0.040170	-0.066368 -0.045046	**Confidence interval**		
0.4056	-	0.3743	0.4107	0.1990	**β**		
0.331298 0.479848	-	0.276901 0.544589	-0.059229 -0.040170	0.174706 0.223372	**Confidence interval**		
-	-0.0545	-0.0475	-0.0531	-0.0563	**α**	**TEJ**	
-	-0.066484 -0.042463	-0.056510 -0.038493	-0.065345 -0.040849	-0.064823 -0.047788	**Confidence interval**		
-	0.3338	0.5328	0.2354	0.1865	**β**		
-	0.237027 0.430514	0.403809 0.661765	0.102208 0.368593	0.164197 0.208844	**Confidence interval**		

Source: Research finding.

$\mathrm{CoVaR}^{\mathrm{bank\,j/bank\,i}}$ and $\Delta\mathrm{CoVaR}^{\mathrm{bank\,j/bank\,i}}$ are calculated using these parameters, and the results are shown in Table 6. As before, $\mathrm{CoVaR}^{\mathrm{bank\,j/bank\,i}}$ represents the value-at-risk of bank j on the condition that bank i is at its value-at-risk level. In addition, $\Delta CoVaR^{\ bank\ j/bank\ i}$ estimates that how much bank i adds to the value-at-risk of bank j if the value-at-risk level of bank i changes from 50% to 5%. For example, Parsian Bank will raise the value-at-risk of Mellat Bank by 6.46% (from the original 5%) whenever the value-at-risk of Parsian Bank changes from 50% to 5%.

Table 6. CoVaR and ΔCoVaR of Bank j Conditional on Bank i

BANK i							
TEJ	**SAD**	**MEL**	**PARS**	**EN**			
-6.43	-7.59	-7.96	-9.08	-	**COVaR(5%)**	**EN**	**BANK j**
-24.11	-14.99	-28.30	-18.39	-	**COVaR(1%)**		
-0.12	-0.11	-0.16	0.00	-	**COVaR(50%)**		

-6.32	-7.48	-7.80	-9.08	-	**ΔCOVaR(5%)**	
-23.99	-14.87	-28.14	-18.39	-	**ΔCOVaR(1%)**	
-7.04	-7.57	-7.69	-	-7.67	**COVaR(5%)**	
-8.07	-11.67	-13.97	-	-11.68	**COVaR(1%)**	
0.00	0.00	0.00	-	0.00	**COVaR(50%)**	**PARS**
-7.04	-7.57	-7.69	-	-7.67	**ΔCOVaR(5%)**	
-8.07	-11.67	-13.97	-	-11.68	**ΔCOVaR(1%)**	
-6.69	-6.71	-	-6.46	-6.92	**COVaR(5%)**	
-12.05	-21.64	-	-8.83	-13.40	**COVaR(1%)**	
0.00	0.00	-	0.00	0.00	**COVaR(50%)**	**MEL**
-6.69	-6.71	-	-6.46	-6.92	**ΔCOVaR(5%)**	
-12.05	-21.64	-	-8.83	-13.40	**ΔCOVaR(1%)**	
-6.85	-	-6.57	-7.59	-6.68	**COVaR(5%)**	
-16.66	-	-20.11	-18.33	-10.08	**COVaR(1%)**	
0.00	-	0.00	0.00	0.0	**COVaR(50%)**	**SAD**
-6.85	-	-6.57	-7.59	-6.68	**ΔCOVaR(5%)**	
-16.66	-	-20.11	-18.33	-10.08	**ΔCOVaR(1%)**	
-	-7.22	-7.44	-6.81	-6.67	**COVaR(5%)**	
-	-20.01	-9.65	-18.52	-13.22	**COVaR(1%)**	
-	0.00	0.00	0.00	0.00	**COVaR(50%)**	**TEJ**
-	-7.22	-7.44	-6.81	-6.67	**ΔCOVaR(5%)**	
-	-20.01	-9.65	-18.52	-13.22	**ΔCOVaR(1%)**	

Source: Research finding.

The results of Table 6 can be summarized in the table below. In this table, the vertical column contains the banks' names, and the rows contains the name of the banks that have the most impact on the mentioned bank. For example, EN, Saderat, Tejarat, and Parsian banks have the most impact on Mellat Bank, respectively. That is, if each of the EN, Saderat, Tejarat and Parsian banks are facing a crisis, Mellat Bank, based on the order, will get the most impacts from the mentioned banks.

Table 7. Direction of Influence

Bank	**Direction of Influence**			
EN	PAR	MEL	SAD	TEJ
PAR	MEL	EN	SAD	TEJ
MEL	EN	SAD	TEJ	PARS
SAD	PARS	TEJ	EN	MEL
TEJ	MEL	SAD	PARS	EN

Source: Research finding.

Table 8. The Quantile Regression Parameters When Regressing the Bank i on the System

TEJ	**SAD**	**MEL**	**PARS**	**EN**	
-0.0438	-0.0387	-0.0352	-0.0526	-0.0530	**α**
-0.053241 -0.034443	-0.045329 -0.032082	-0.042112 -0.028316	-0.066809 -0.038345	-0.074142 -0.031848	**confidence interval**
0.8476	0.8990	0.7948	0.6254	0.5416	**β**
0.539108 1.156211	0.600493 1.197590	0.426422 1.163163	-0.064421 1.315315	-0.054571 1.137553	**confidence interval**

Source: Research finding.

Table 9. CoVaR and ΔCoVaR of Bank j Conditional on the System

TEJ	**SAD**	**MEL**	**PARS**	**EN**	
-7.04	-6.68	-6.01	-7.22	-6.99	**COVaR(5%)**
-23.55	-24.16	-32.79	-11.04	-13.36	**COVaR(1%)**

0.00	0.00	-4.64	0.00	-0.16	**COVaR**(**50**%)
-7.04	-6.68	-1.37	-7.22	-6.84	**ΔCOVaR**(**5**%)
-23.55	-24.16	-28.16	-11.04	-13.20	**ΔCOVaR**(**1**%)

Source: Research finding.

Finally, in Tables 8 and 9, we show the results of the entire system's impact on each bank. Here we study the likelihood of each of the selected banks getting affected in the event of a crisis throughout the system. Table 9 shows the results of each bank's regression on the system variable in terms of coefficients and confidence interval.

$\mathrm{CoVaR}^{\mathrm{bank\ i/system}}$ and $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i/system}}$ are presented in Table 9 for quantiles numbers 1 and 5. $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i/system}}$ states the amount of risk that each bank (i) is exposed to. In other words, $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i/system}}$ shows the sensitivity of bank i to the criticality of the entire banking system. For example, according to Table 9, the criticality of the entire banking system is 7.04%, which is added to the value-at-risk of 5% of Tejarat Bank when the value-at-risk level of the entire financial system changes from 50% to 5%. Table 9 results indicate that why Mellat banks is less exposed to systemic risk, for which $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i/system}}$ is noticeably less than $\Delta\mathrm{CoVaR}^{\mathrm{bank\ i/system}}$ for other banks.

These results indicate that PARS and TEJ are more volatile or risky banks since they are more sensitive than other banks to the system going into distress. E.g. the system contributes -6.68% to 5% VaR of SAD compared to -7.22% to 5% VaR of PARS when the system goes into distress. Of course, the above results are true at the quantile level of 5%. For the quantile level of 1% we have obtained different results as we found Mellat and Saderat banks much more risky and more sensitive to crises in the entire banking system, compared to other banks.

In other words, in this case, the results indicate that MEL and SAD are more volatile or risky banks since they are by far more sensitive than other banks to the system going into distress. E.g. the system contributes -13.20% to 1% VaR of EN compared to -28.16% to 1% VaR of MEL when the system goes into distress. Therefore, by changing the level of the quantile under study, both the amount of risk and the order of sensitive banks change.

Conclusion

The $CoVaR$ measure is a way to better understand how risk spreads in the financial system. This measure is an indicator of systemic risk and due to some of the following advantages, the use of this method is expanding: 1. The results can be easily analyzed. 2. $CoVaR$ does not require complex data sets. 3. $CoVaR$ can be used with other risk indicators. This paper analyzed the Iranian banking system based on the data of five major banks of the country that are listed on the Tehran Stock Exchange. They were studied separately without reviewing their communications with the banking systems of other countries, and it is observed that each bank, regardless of the size and its individual risk, affects the systemic risk. In this paper, systemic risk was studied from three different perspectives: 1- The systemic impact of each of the studied banks on the entire banking system. 2- Mutual effects of the crisis in each bank on other studied banks. 3- The impact of the entire banking system's risk on each of the selected banks.

In this study, it was observed that the amount of individual risk of each bank is not proportional to the contribution of systemic risk of the bank. Tejarat and Parsian banks with the values of -18.15 and -11.72, respectively, have the highest and lowest individual risks among banks at the quantile level of 1%. At the same quantile level, Mellat and EN banks have the highest and lowest systemic risks in the banking system with values of -13.35 and -6.66, respectively. In other words, a high value of VaR for a bank does not imply a substantial contribution of the bank in systemic risk.

Since risk spread and systemic importance of an institution is of central importance compared to that institution's individual risk value from the policymakers point of view, thus in addition to estimating value at risk (VaR), there should be initiations regarding appropriate methods for systemic risk calculations and introducing institutions of higher systemic risk effects.

It is observed that banks ranking according to their individual risk calculated by VaR does not conform to the systemic risk values obtained from $COVaR$. Based on VaR criterion, Parsian and Tejarat Banks have the highest risk, while according to the $CoVaR$ criterion, in the case of a crisis in the entire system, Parsian and Tejarat Banks are most affected by the crisis. While Parsian, Mellat, EN, Tejarat, and Saderat Banks mostly contribute to the crisis of the banking system, respectively. Investigating the risk contribution of banks and the risk exposure of each of them in the existence of a crisis in the entire system, the results show that Mellat bank is the most stable bank and less susceptible to the crisis in the system. However, Parsian and Tejarat banks are very sensitive to a crisis in the whole system. Of course, the amount of systemic risk of the entire banking system due to the crisis in each of the studied banks, i.e. $\Delta \mathrm{CoVaR}^{\mathrm{sys/bank\,i}}$ changes by changing the amount of quantile. Besides, the primacy of the systemic importance of each bank over others, in terms of creating risk for the entire banking system, changes by the change of quantile.

The results of the articles of Eivazloo and Rameshg (2020), Abrishami et al. (2019), and Rastegar and Karimi (2016) showed that big banks do not necessarily have a greater systemic risk. The results of this article are following the findings of the mentioned articles and it is observed that in some cases the systemic risk caused by smaller banks is more than the systemic risk caused by bigger banks. Hosseini (2014) showed that the financial institutions under study have significant differences in terms of impact on systemic risk and their impact on systemic risk is not uniform. In this paper, the results showed that the amount of risk in Quantile 5% and 1% are completely different from each other, and the rank of financial institutions in terms of affecting and getting affected by the risk, changes by changing the amount of Quantile. In addition, the difference in the amount of systemic risk is due to the difference in the method of risk calculation and the period and the data employed.

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