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Modified systemic risk model with ΔCoVaR approach in banking system with an Emphasis on Bank Indicators

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ABSTRACT

The present study presents the revised systemic risk model with the Changing conditional value-at-risk (ΔCoVaR) approach in banking network with an emphasis on bank indicators. Systemic risk investigates the potential capacity of financial crisis spread among banks and ultimately the real sector of the economy through simultaneously increasing the fat tail of loss distribution. This is a descriptive-analytical research in terms of method and a developmental/applicative study in terms of purpose. The research time zone is 2009/03/21-2021/01/19. The research data includes the weekly average stock price of seven banks (Mellat, Tejarat, Saderat, EN Bank, Parsian, Karafarin, and Sina) listed in stock exchange and the weekly average of the general stock market index from Rahavardnovin system, and data related to the banks' financial metrics are extracted from the financial statements of the banks in the Codal website.

To measure each bank's share in systemic risk, the measure (ΔCOVaR) is employed. We show the better fit of ΔCoVaR for measuring risk compared to VaR and CoVaR models. The ratings of the investigated banks are tested by means of two criteria (RMSE) and (MAE) and it is concluded that in some banks, the crisis has higher destructive effects on the entire financial system than that in other banks. Finally, the association between systemic risk and the financial parameters of the investigated banks is reviewed and it is concluded that the improvement of the capital adequacy ratio (CAR) has an inverse and significant relationship with systemic risk.

Keywords:

Quantitative Modeling of Systemic Risk, Delta Conditional Value-at-Risk (ΔCoVaR), Dynamic Conditional Correlation, Multivariate GARCH Model.

1. Introduction

The occurrence of systemic risk is one of the most terrible events in the banking network. Although this event in the banking industry may be considered equivalent to a fire in the crowd, unlike fire, the term systemic risk does not have a specific and precise definition. Moreover, unlike firefighters who are rarely responsible for starting or spreading fires, banks are the key culprits of systemic risk due to their negligence (Kaufman and Scott, 2003). Systemic risk in banking is appeared by very high correlation and total simultaneous banking failures in one country, several countries, or all countries. Systemic risk refers to a chain reaction in the form of connected dominos. Accordingly, it is called systemic due to having a systemic effect on the entire system and it is quickly transmitted throughout the entire capital market or the whole economy of a country as well as influencing it.

The systemic risk may not be estimated and analyzed just through separately calculating the individual risk of each bank. Even though it is assumed that all the current institutions have little risk, the presence of herding behavior among financial institutions may lead to systemic risk for the whole group (Arias, Mendoza & Reyna, 2010). In fact, when banks are independently assessed, they may perform well based on micro prudential approach; however, the entire banking system may be subject to crisis and damage; since the occurrence of a crisis in a bank and its spread to the others – which may have relatively good performance - can be followed by the collapse of the banking system and even the whole financial system. Thus, the new approach in monitoring financial systems focuses on the macro prudential approach with the aim of monitoring and reducing systemic risk (Davis & Karim, 2009; Bisias et al., 2012).

2. literature

The occurrence of financial crises over the years 2007-2009 and their resulting experiences and achievements revealed that capital adequacy regulations based on the regulation of Basel II standard would not manage to fully protect banks and credit institutions against possible losses. Hence, while publishing the framework of interaction with global and domestic systemically important banks (SIBs), the Basel Committee on Banking Supervision (BCBS) emphasized the need to have separate capital coverage to deal with the risks caused by SIBs. An SIB stands for an institution in which the occurrence of a crisis has important effects on macro conditions of domestic or even international economy due to having characteristics like size, market share, domestic communication and entanglement, cross-border activities, complexity, and so on[1]. Given characteristics such as high degree of leverage, mismatched maturity of assets and liabilities, the necessity to maintain the general and permanent trust of depositors and society members, the possibility of transmission of banks' problems to each other, and finally direct effect on the macroeconomic conditions, banking activity inevitably requires risk acceptance, which can affect the financial and economic system at the domestic or even international level depending on the dimensions, complexity of activities, the level of importance (risk) of the bank's system, and in case of lack of proper supervision.

Iran is classified among countries with bank-based financial system. According to the report of the proposed production promotion package (published by the Chamber of Iran - 2019), about 98% of the volume of 704 enterprises financing in 2017 has been financed through the banking network and only 2% through the capital market channel. The banking system's high share in provision of funds needed by the country's different economic sectors indicates the bank-based financing system of Iran's economy. In such systems, the banking system's shortcomings and inefficiencies directly and indirectly affect the trend of micro and macroeconomic variables severely. Any inefficiencies and defects in the process of attracting and allocating resources by banks not only leads to their loss, but also has destructive effects on the country's economic growth and development. In the last two decades On the other hand, the country's banking network has faced the growth and development of private banks and authorized (and sometimes unauthorized) credit institutions. Based on the Central Bank website's statistics and information (banking supervision department - authorized banks and monetary institutions[2]), 36 banks and credit institutions are operating in Iran at present. It is worth noting that in the past few years, the bankruptcy of some credit

[1] The Central Bank of the Islamic Republic of Iran - a framework for interacting with systemically important domestic banks - April 2015 (Publications of the Basel Committee on Banking Supervision - 2012)
[2] https://cbi.ir/BanksInstitutions

institutions[3] - sometimes even having the license of the Central Bank - caused the dissatisfaction of a large number of these institutions' depositors and customers and imposed huge economic, social, and political costs on the society[4]. Besides, in recent decades, the banks' competition with each other to maintain their market share has increased, and given the central role of the country's banking network in financing the production sector, any disruption in its performance affects the production sector and thus other macroeconomic variables. According to the Central Bank's statistics, at the end August 2022, the balance of the banks' debt to the Central Bank was equal to 1,709 thousand billion Rials, i.e. a growth of about 37.6% compared to the previous year. Meanwhile, in August 2022, the banks' total legal reserves in the Central Bank was equal to 5,663 thousand billion Rials. In fact, despite the very large liquidity at macro level (at the end of December 2021, liquidity amounted to 54,017 thousand billion Rials), we are facing a liquidity crunch in the country's banking network, and any bank run[5] and depositors' influx into the banking network may cause a crisis in banking system of the country. As the Central Bank reports[6], the performance of the Rial interbank market at the end of 2020 amounted to 186,888,022 billion Rials. In the meantime, the private banks' share in the deposit capacity was equal to 60% and the share of banks subject to Article 44 of the Constitution was equal to 13%. The above statistics show the structure of banks' dependence in the interbank market, indicating that the occurrence of a crisis in any of the country's banks, particularly private banks subject to the general policies of Article 44 of the Constitution, may result in a crisis in the entire banking network of the country. Accordingly, the systemic risk estimation of the country's banking system is of paramount importance. On the other hand, the CAR[7] is one of the key indicators in any country's banking system. In fact, the bank's risk and confidence level and protection of bank deposits are measured by the CAR. In total, in the investigation of the situation of 23 Iranian banks in 2020 (five government banks, seventeen private and non-government banks, and one credit institution), only six banks have achieved a CAR of 8%, and the other 17 have nonstandard CAR. It is worth noting that among these 23 banks, eight have a negative CAR, six have a CAR between zero and 4 percent, three have a CAR between 4 and 8 percent, and only six banks have a CAR of 8 percent or more[8]. The inappropriate state of CAR of the country's banks, the increased balance of banks' outstanding claims in recent years, and the bank customers' increased credit defaults have resulted in an increased overdraft of the banks from the unstable resources of the Central Bank with a 34% cost. Besides other structural issues of Iran's economy (like high liquidity growth with an average of 25% per year during the past forty years, high inflation, fluctuating and negative recent economic growth (Iran's average economic growth in the last twenty years is about 2.8%), implementation of large economic projects such as Mehr housing and obliging the financial burden of such projects to the shoulders of banks, directed credits, currency crises due to sanctions, and ordered change of bank interest rate), this increases the possibility of a crisis in the banking system, clarifying the need to pay attention to the systemic risk. Based on the aforementioned descriptions, since the cost of bank bankruptcy, if occurs, is very high given the international experiences, provision of early-warning systems distinguishing between high-risk banks I (domestic banks with the importance of systemic risk) and low-risk banks in the country's banking network is of great importance.

The main question of the present study is whether systemic risk may be explained through the development of conditional value at risk (CoVaR). Given the question raised, the research hypotheses include 1- The systemic risk of the entire market (capital) is high dependent on the banking sector, 2- In some banks, the crisis has more destructive effects on the entire financial system compared to that in other

[3] Such as Iranian, Afzal Tous, Arman Vahdat, Samen-al-Hojaj, and Mizan Financial Institutions

[4] Estimates indicate that an amount of 35,000 billion Tomans has been spent by the government during the years 2017 and 2018 to solve the credit institutions' crisis. In other words, an amount of about 450,000 Tomans (about 130 dollars at the rate of 3,500 Tomans - the average dollar price of 2017 and 2018) has been paid from the pocket of each Iranian.

[5] bank panic

[6] Central Bank's website – statistics and data – banks' performance in the inter-banking market at the end of 1398 (Solar Year)

[7] The capital adequacy ratio (CAR) actually refers to "the result of dividing the basic capital by the total weighted assets by the risk coefficients in percentage". Based on the regulations of the "Basel I" international committee on banking supervision, a bank's minimum standard CAR should be 8% to ensure that the bank does not go bankrupt and the risk factor ratio is created. In regulations of the "Basel II", the minimum CAR has increased to 12%.

[8] Research findings

banks, 3- There is a relationship between systemic risk and bank financial characteristics.

3. Research Background

Systemic risk was first investigated in the early 1990s with the enactment of the "Federal Deposit Insurance Corporation Improvement Act of 1991". From this time on, the definition and recognition of systemic risk attracted attentions; however, the majority of systemic risk researches were carried out after the financial crisis of 2007-2009.

In their research entitled *Lifecycle of Systemic Risk*, Berger Allen N, Sedanov John (2021) addressed the formation of systemic risk before the crisis, the behavior of systemic risk, and policymakers over and after the crisis period. Aiming at measuring and forecasting systemic risk in global financial markets besides creating a business decision model for investors and financial institutions, Liu et al. (2020) combined GJR-GARCH (1,1), Copula-GARCH, and component expected shortfall (CES) models. The use of copula factor models enables systematic estimation of common models, thus reducing the amount of calculations. Andersson &Lindskog (2019) examined the forecasting ability of the DCC-GARCH model. The results revealed the accurate prediction of volatility movement in the conditional correlations by this model, although the values predicted are not very correct and are less than the actual values. By means of the Copula-DCC-GARCH model, Wanat & Denkowska (2018) analyzed the dependence among eight insurance companies, including five European companies and three American, Canadian, and Chinese companies, as well as their share in systemic risk in the insurance sector. According to the results, all insurance companies had a positive correlation, stronger in times of turbulence in the global markets. AD Clemente (2018) used an extreme value theory (EVT) model to analyze the share of a financial institution in the formation of systemic risk and clarified the association between the systemic risk of a financial institution and that of the entire financial system. Karimalis & Dumitrescu (2017) examined the systemic risk share in large European banks according to the Copula model and COVaR. Brownless & Engle (2016) introduced SRISK for measuring the systemic risk share in financial companies and accordingly presented a ranking for institutions at different stages of crisis. Lin et al. (2016) employed CoVaR, MES, SRISK, and other methods to study the level of exposure of financial institutions to systemic risks and the risk share of each institution in the financial market; moreover, they measured the data of financial institutions in Taiwan to empirically measure it. Adrian & Brunnermeier (2016) utilized the ΔCoVaR method in order to measure the severity of transmission of a financial institution's systemic risk to other financial institutions and the financial institutions' systemic risk share. Derbali and Hallara et al. (2015) used the MSE model for measuring the systemic risk of European financial institutions. To show the liquidity risk, Grieb (2015) employed a nonlinear factor model and logistic regression model to exhibit the probability of effect of systemic risks on hedge funds. Reboredo & A Ugolini (2015) used the CoVaR method to measure the systemic risk of European regional markets' sovereign debt crisis risk after the Greek debt crisis, fining the similar sovereign risk in all pre-crisis periods. Banulescu & Dumitrescu (2015) utilized the component expected shortfall (CES) measure to identify systemically important financial institutions in the United States. Girardi and Ergun (2013) revised the definition of CoVaR and defined an organization's systemic risk as the changes in CoVaR in financial crises, then investigating the association between systemic risk and its characteristics in four financial industry groups. Derhmann and Tarashev (2011) used Shapley value analysis to measure the systemic importance of each institution. Through simulating the banking system, this approach defines each bank's risk share as a weighted average of the effect added by it to each subsystem. Yu et al. (2010) employed a DCC-GARCH model to analyze the correlation of 11 markets. Their results revealed a strong transmission effect from the US economy to the Asian countries' economies in the 2007 crisis. Adrian & Brunnermeier (2009) presented the CoVaR method for calculating the systemic risk in the US financial market. In order to calculate the individual firms' contribution to systemic risk, they defined the concept of ΔCoVaR as the difference between the financial system's CoVaR under the condition that the institution in question is facing crisis and the same financial system's CoVaR under normal condition.

Concerning the background of domestic research on the presentation of the systemic risk model with the approach of changing the conditional value at risk

(CoVaR) in the banking network, a summary of the research is as follows: Mirfeyz Fallah Shams et al. (2022) entitled *Systemic risk transmission in financial markets* have identified transmission and its effects in Iran's financial markets through using simultaneous Multi-Garch models and covariance changes. The results revealed that regardless of the first period, at the beginning of the period, the bank market's reaction to the shocks of exchange rate volatility is positive and this direct relationship gradually falls until the sixth period, tending to turn from positive to negative. Furthermore, according to the results, turbulence and shock of one market affect another market. Jabal Ameli et al. (2020) examined the correlation between the selected banks and the dynamic conditional correlation model to identify systemically important banks with Shapley CoVaR method. The results suggested that the use of DCC-GARCH-t-student model is preferable to DCC-GARCH-normal model. Eyvazlou and Ramashg (2019) estimated the systemic risk for 11 commercial banks by two methods of component expected shortfall (ES) and conditional value at risk (CoVaR) and through using the dynamic conditional volatility. In accordance with the MES (Marginal Expected Shrtfall), Dey, Sarmayeh, Sina, EN, Ansar, Mellat, Tejarat, Saderat, Karafarin, Pasargad, and Parsian Banks have the greatest impact on systemic risk, respectively; while according to the average CoVaR criterion, Sarmayeh, Dey, Sina, Ansar, EN, Saderat, Mellat, Tejarat, Parsian, Pasargad, and Karafarin Banks have had the greatest impact on systemic risk. Abrishami et al. (2019) calculated the systemic risk for 15 banks listed in the capital market for the period 2015/05/04 to 2018/09/05 based on MES, ΔCoVaR, and SRISK criteria. After calculating the indicators, by means of correlation and regression analyses, the impact of some macroeconomic variables on the indicators was estimated. As the results indicated, the systemic risk does not just focus on big banks, but small banks also play a role in its emergence and spread. Hekmati Farid et al. (2018) estimated the systemic risk through applying the CoVaR method presented by Adrian and Brunnermeier and by means of the data of the stock exchange, insurance, and bank's financial departments over the years 1995-2015. The post-hoc tests indicate a significant difference between the systemic risk and the algebraic sum of the risk of each of the financial sectors of bank, insurance, and stock market. Mahdavi Kalishemi et al. (2017) studied the systemic risk 17 banks in Iran's banking sector using the criterion of changing the CoVaR. Based on the results, Middle East Bank (MEB) and Sarmayeh Bank have the highest and lowest changes in conditional value at risk, respectively. Danesh Jafari et al. (2017) calculated the final expected deficit index with the help of the dynamic conditional correlation (DCC) model and ranked them in order to examine the systemic risk of the banking system. According to the results of the paper, the global financial crisis has not affected the domestic banks. Since Mellat and Saderat Banks have the highest value of assets, they were responsible for the largest share in the occurrence of systemic risk. Danesh Jafari, Botshekan, and Pashazadeh (2016) calculated the value at risk by the dynamic conditional correlation model and quantile regression for studying the systemic risk in the banking system. According to the results, compared to quantile regression, dynamic correlation model presents more realistic results. In their paper, Rastegar and Karimi (2015) estimated the systemic risk in the banking industry with the CoVaR approach. Their results suggested that in the examined period, Tejarat, Mellat, Ansar, Saderat, Post, Parsian, and EN Banks respectively had the greatest impact on the entire system in terms of the systemic risk.

4. Research Methodology

This is a quantitative research categorized in the developmental/applicative researches in terms of purpose. Moreover, it is an ex post research in terms of the time of occurrence carried out with a descriptive regression type method, and given the presence of various variables in the model, the relationships are examined in the DCC-t-Student-GARCH model. The statistical population and geographical scope of the present research include Iran's banking industry. The scope of this subject, on the one hand, investigates the regulatory authorities' measures in explaining and measuring systemic risk, and on the other hand, refers to managers' risk-taking decisions. The time zone and research data during the period of 12009/03/21-2021/01/19 have been collected from the financial statements of the banks, and the data related to the price (weekly average) of the selected banks' shares have been extracted from Rahavard Novin.

The methodology of the present research includes two general steps:

The first step: Estimation of ΔCoVaR measure as the systemic risk measure proposed by Adrian & Brunnermeier (2016) for seven banks listed in the capital market based on DCC-t student-MGARCH approach

The second step: Examining the association of the aforementioned measure with the bank characteristics including leverage ratio, size (logarithm of capital), and the ratio of cash assets to total assets with the help of panel data regression

Conditional value at risk (CoVaR)

According to the definition of Adrian & Brunnermeier (T.Adrian & M.K Brunnermeier, 2016), $CoVaR_q^{(j|i)}$ (conditional value at risk) is the VaR_q^j of GM institution provided that a systemic event affects the IM institution. According to the definition, $CoVaR_q^{(j|i)}$ is equal to the q^{th} quartile of the conditional probability distribution of GM return as below:

$$\Pr\left(R^i \leq CoVaR_q^{(j|C)\,(R^i)} \,|C(R^i)\right)$$

Changes in conditional value-at-risk, the systemic risk measure

Adrian & Brunnermeier first employed the CoVaR difference as a systemic risk measure. Accordingly, the symbol ΔCoVaR is defined as the difference between the CoVaR of the financial system *j* when the financial institution *i* is in an emergency and chaos state (when reaching its unfavorable level of value at risk (5%)) and the CoVaR of the same institution is in normal conditions (when the i^{th} institution is placed in the middle state, i.e. 50%):

$$\Delta CoVaR_q^{(j|i)} = CoVaR^{j|Xi=VaR_q^i} \_ \, CoVaR^{j|Xi=median^i}$$

Dynamic Conditional Correlation (DCC)

Conditional correlation models indeed stand for nonlinear combinations of univariate GARCH models. In these models, conditional variance and conditional correlation matrix are separately specified. The conditional variance matrix (H_t) of this group of models is specified by a hierarchical process, so that initially an average equation that may be in the form of an ARMA model is estimated for each return series to select a single-variable GARCH model for the conditional variance of all assets from the residuals resulting from these residuals (these residuals are called return series with zero mean and covariance matrix H_t) and the DCC matrix is then modeled based on the conditional variance of the first stage.

A type of MGARCH model is introduced by Bullerself (1990), in which the conditional correlations are fixed (CCC model) and the conditional covariance are thus a proportion of the product of the corresponding conditional standard deviations. The fixed conditional correlations may seem unrealistic. Christodolakis and Sashel (2002), Engle (2002) and Sesoui (2002) have proposed the CCC model's generalized form through making the conditional correlation matrix dependent on time. This model is known as Dynamic Conditional Correlation (DCC) model. In the DCC model proposed by Engle (2002), the conditional variance-covariance matrix (H_t) may be decomposed as:

$$Ht = Dt\ Rt\ Dt$$

$$Dt = diag\left(h_{11t}^{\frac{1}{2}} \dots \dots .. h_{NNt}^{\frac{1}{2}}\right)$$

and Rt is the time-varying correlation matrix.

Qt refers to a symmetric N × N positive definite matrix so that:

$$Q_t = (1- \alpha - \beta)\,\bar{Q} + \alpha u_{t-1}\, \acute{u}_{t-1} + \beta Q_{t-1}$$

$u_{it}=\varepsilon_{it}/\sqrt{h_{it}}$ and $\bar{Q}$ is the unconditional variance u_t matrix with N × N dimensions. Besides, α and β are nonnegative scalar parameters satisfying the condition α+β<1. The limits stated for α and β parameters guarantee that the Q_t is positive and definite and this is a necessary and sufficient condition for *Rt* matrix to be constant definite (Engle & Shepherd, 2001).

Investigating the relationship between the introduced measure and the bank characteristics

After calculating the mentioned measure, its association with bank characteristics is examined, including leverage ratio, size (logarithm of capital), and the ratio of cash assets to total assets with the help of panel data regression. In the panel data model, it is assumed that the observations are for N individuals over period T. To indicate these two dimensions, the two indices *i* and *t* are used, i.e.:

$Y_{it,}$ i= 1,….., N, t= 1, ….., T

Now, the general equation for individual *i* at time *t* can be expressed as the equation below:

$$Y_{it} = \beta_{1it}X_{1it} + \beta_{2it}X_{2it} + \cdots + \beta_{kit}X_{kit} + \beta\upsilon_{it} = \acute{X}\iota t\beta_{it} + \upsilon_{it}\ \beta_{kit}$$

β_{kit} stands for the parameters to be estimated and $\acute{X}\iota t\beta_{it}$ shows the row vector (1×*K*) of explanatory variables and β_{it} is the column vector of regression coefficients. On the other hand, in some models it must be known whether the model will include the intercept or not (it is obvious that both models may be considered). If the general intercept is considered for regression, $X_{1it} = 1$ would be for all i-s and t-s, thus we have:

$$Y_{it} = \beta_{1it}X_{1it} + \beta_{2it}X_{2it} + \cdots + \beta_{kit}X_{kit} + \beta\upsilon_{it} = \beta_{1it} + \tilde{\acute{X}}\iota t\tilde{\beta}_{it} + \upsilon_{it}\ \beta_{kit}$$

The mentioned equations are the most general problem statement in panel data regression, implying that each person has his own reaction coefficients in each period. Since the current research does not employ the questionnaire tool to collect data, the discussion of checking the reliability is ruled out. Modeling related to this study has been performed using R software.

Table (1): Summary of the modeling in this research

Row	Research modeling steps	The reason for calculation and estimation	Calculation approach and method
1	Data mining: data cleaning	Eliminating some research limitations in the field of missing data	imputation analysis/multiple imputation
2	Descriptive data analysis	Summarizing the information and explaining the dataset characteristics/checking the assumption of normality of the research variables	Central parameters - Dispersion/ Jarque-Bera Test statistic
3	Stationarity test of research variables	Checking the occurrence of the false regression problem	Generalized Dickey-Fuller test
4	Checking the first research hypothesis	The banking sector is highly dependent on the capital market.	Correlation: conditional/unconditional
5	Estimating risk measures with three approaches	Calculating the value at risk, currency at conditional risk, changes in CoVaR	VaR - CoVaR - ΔCoVaR
6	Checking the second research hypothesis /ranking the banks based on the ΔCoVaR measure	The occurrence of crisis in some banks has higher destructive effects compared to that in some other banks.	Root mean square error RMSE/mean absolute error MAE
7	The association between banks' financial characteristics and ΔCoVaR	Can the data panel method be employed to investigate the association between banks' financial characteristics and systemic risk measure?	Lagrange test
8	Estimating Panel data model	Choosing between Pooling and Panel strategies	F-Limmer's test (Chow)
9	Rejection of H_0 hypothesis in F-Limer test	Fixed or random effects?	Hausman test
10	Checking the third research hypothesis/the association between the banks' financial characteristics and ΔCoVaR	Is there a significant relationship between the systemic risk measure and the banks' financial characteristics?	Panel Data Regression/Fixed Effect Model

5. Research Findings

5-1. Descriptive Data Analysis

Based on the table below, the highest and lowest average stock returns in the reviewed period are for Sina and Parsian Banks, respectively. In accordance with the standard deviation index, stock return of Sina Bank has the most volatility and that of Mellat Bank has the least volatility. According to Jarque-Bera's test statistic, the variables investigated in this study do not have a normal distribution; i.e., the null hypothesis of the normality of the study variables is rejected.

Table 2: Variables' descriptive statistics - stock returns of selected banks, bank index, and stock market index (2009/03/21-2021/01/19)

Jarque-Bera Test	Standard error	Kurtosis	Skewness	Range	Maximum	Minimum	Median	Standard deviation (SD)	Mean	Observation	
77.71	0.0022	1.5528	0.3782	0.3745	0.1927	-0.1818	-0.0021	0.0543	0.0025	615	EN Bank
36.36	0.0022	1.1663	-0.0815	0.3339	0.1640	-0.1699	-0.0025	0.0536	-0.0017	615	Parsian
40.04	0.0019	0.9140	0.4184	0.2876	0.1524	-0.1351	0.0003	0.0473	0.0041	615	Karafarin
61.96	0.0023	1.4625	0.2423	0.4046	0.2067	-0.1979	0.0000	0.0561	0.0059	615	Sina
54.58	0.0017	1.3943	0.1904	0.3043	0.1509	-0.1534	0.0005	0.0422	0.0050	615	Mellat
95.01	0.0019	1.5958	0.5262	0.3142	0.1738	-0.1404	-0.0008	0.0482	0.0032	615	Tejarat
91.13	0.0020	1.5306	0.5391	0.3427	0.1891	-0.1536	0.0000	0.0500	0.0047	615	Saderat
96.05	0.0012	1.7563	0.3893	0.2114	0.1133	-0.0980	0.0011	0.0289	0.0049	615	Bank Index
94.52	0.0010	1.7653	0.3588	0.1996	0.1077	-0.0919	0.0046	0.0255	0.0070	615	General Index

5-2. Checking the first hypothesis: the banking sector is highly dependent on the capital market

To check the mentioned hypothesis, the concept of correlation with two unconditional and conditional approaches is employed.

5-2-1. Unconditional correlation

In this part of the research, the unconditional correlation model (Pearson's correlation coefficient) is used. To this end, the association between the bank index return and the total index return is investigated. Bank index return is defined as an independent variable and total index return as an explanatory variable.

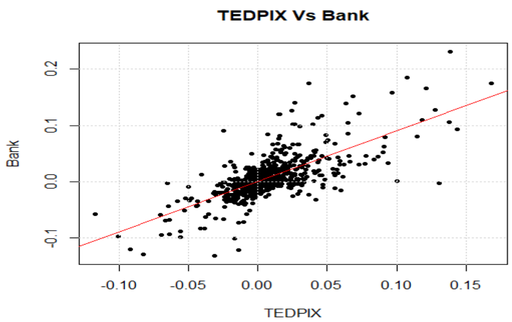

Fig. 1: Unconditional correlation between bank index return and total index return

According to the above table and figure, there is a significant positive association between the correlations of the bank index return and the total index return. In case of taking the root of the multiple R-squared values, the unconditional correlation is estimated to be about 0.7. I.e., there is a positive correlation of about 70% between the total index return and the bank index return.

5-2-2. Conditional correlation

Many changes have been exhibited by the conditional correlation between banking sector stock return and total index return (market changes) in the range of 0.1 to 0.8, besides having several sharp drops. Based on the existing researches, the conditional correlation increases over the financial crises and the share price of the banking sector has significantly increased simultaneous with the fall of conditional correlation.

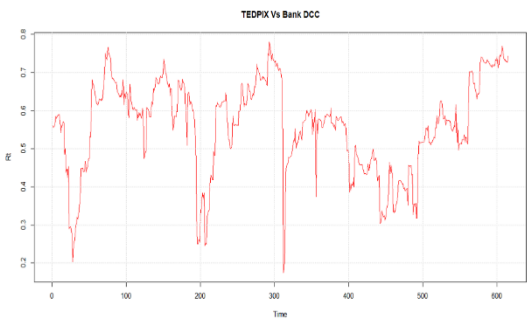

Fig. 2: Conditional correlation between bank index return and total index return

5-3. Checking the second hypothesis: in some banks, the crisis has higher destructive effects than that in other banks

According to the above table, banks have different changes in CoVaR as a measure of systemic risk. The output of this table may be employed by stakeholders like the Central Bank and the capital market as the ranking the systemically important banks. This table suggests that if a negative event occurs in Parsian Bank, it will have a systemic effect more than that in EN Bank, indicating that the traditional look at the issue of risk and risk-based legislation of a bank in isolation (i.e., considering the risk of a bank just with itself) will lead to additional risk-taking along the systemic risk dimensions. In fact, one of the characteristics of the use of ΔCoVaR is its focus on the association between a bank and the financial system, while traditional risk calculation methods such as VaR focus on the risk of an institution alone. Based on Table 3, this may be investigated from another viewpoint. The two banks may have the same VaR (at three decimal places) (such as Tejarat and EN Banks), but the significant point is that when calculating systemic risk based on the Delta CoVaR (ΔCoVaR) criterion, Tejarat Bank has more systemic risk compared to EN Bank. In other words, the identical risk parametric criteria like VaR do not result in the existence of the identical ΔCoVaR as a systemic risk measurement criterion.

Fig. 3 shows the weak association between the banks' risk in isolation, exhibited by the horizontal axis and with the VaR criterion, and the related role of the banks in the systemic risk, exhibited by the vertical axis with the ΔCoVaR symbol. This is in line with one of the main findings of Adrian & Brunnermeier (2016), claiming that in case of the lack of correlation between VaR and ΔCoVaR in cross-sectional data for an institution, these two measures do not present identical information.

Table 3: Estimation of VaR, CoVaR, and ΔCoVaR at 95% confidence level

Rank based on VaR	VaR Measure	Bank's Name	Rank based on VaR	CoVaR Measure	Bank's Name	Rank based on ΔCo VaR	ΔCo VaR Measure	Bank's Name
1	0.0565	Saderat	1	0.080	Mellat	1	0.0177	Karafarin
2	0.0601	Mellat	2	0.085	Karafarin	2	0.0194	Mellat
3	0.0663	Karafarin	3	0.0956	Saderat	3	0.0380	Saderat
4	0.0666	Tejarat	4	0.1070	Tejarat	4	0.0385	Tejarat
5	0.0675	Sina	5	0.1159	Sina	5	0.0472	Sina
6	0.0779	EN Bank	6	0.1362	EN Bank	6	0.0537	EN Bank
7	0.0893	Parsian	7	0.1472	Parsian	7	0.0541	Parsian

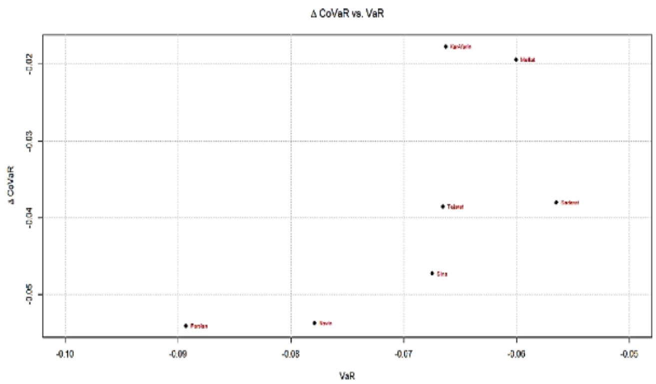

Fig. 3: Relationship between VaR and ΔCoVaR

5-4. Estimation of the ΔCoVaR criterion based on the DCC-MGARCH approach according to the two RMSE and MAE criteria:

Since the current research uses the multiple imputation statistical technique and predictive mean matching (PMM) method in the package Mike format in the R software to solve the challenge of missing data regarding the period when the bank's shares have no information on the stock trading board (in the term of the market, the symbol is closed) and no price is reflected on the trading board, the ranking is now reviewed by means of the two RMSE and MAE measures based on the ΔCoVaR criterion. The goal of revision is to know whether the imputation method used in the research is correct or not.

5-4-1. Root Mean Square Error (RMSE)

Means Square Error is one of the most known and common loss functions in regression analysis, called MSE for short. This loss function[9] calculates the root mean square of the distance between the forecasted and actual values. The way to calculate it is observed below:

$$MSE=\frac{\sum(Yi-Y\acute{i})\ \hat{}2}{n}$$

In case of taking the root from the MSE loss, another loss function called "Root Means Square Error is made, abbreviated as RMSE. Root mean square error, root mean square deviation, or RMSE shows the difference between the value forecasted by the model or statistical estimator and the actual value.

Table 4: Rating test of banks based on systemic risk calculated by DCC-MGARCH based on RMSE criterion

Rank	Name of the Bank	RMSE
1	Mellat	0.0872
2	Karafarin	0.1009
3	Tejarat	0.1028
4	Parsian	0.1096
5	Saderat	0.1112
6	EN Bank	0.1133
7	Sina	0.1184

[9] Most algorithms in "machine learning" operate based on the minimization/maximization of the "objective function". The group of objective functions supposed to be minimized are known as "Loss Functions".

5-4-2. Mean Absolute Error (MAE)

Another loss function is the mean absolute error, abbreviated as MAE. Like MSE, this loss function uses the distance between the forecasted and actual value as a criterion, but not considering the direction of this difference. Hence, in calculating the MAE error, only the extent of distance and not its direction is used.

Thus, MAE calculates the mean absolute value of the difference between the forecasted and actual values. The method of obtaining MAE is presented in the following equation:

$$MAE=\frac{\sum|Yi-\widehat{Yi}|}{n}$$

Table 4: Rating test of banks based on systemic risk calculated by DCC-MGARCH based on MAE criterion

Rank	Name of the Bank	MAE
1	Mellat	0.0857
2	Karafarin	0.0968
3	Tejarat	0.0984
4	Saderat	0.1048
5	EN Bank	0.1080
6	Parsian	0.1084
7	Sina	0.1120

5-5. Checking the third hypothesis: there is an association between systemic risk and bank financial characteristics

Three characteristics are defined as independent variables for this research: 1- Leverage ratio (the ratio of shareholders' equity to total assets) $TE/_{TA}$, 2- Size (logarithm of capital) $Log\ Cap$, and 3- Ratio of cash assets to total assets $CA/_{TA}$, and systemic risk measure ΔCoVaR is defined as dependent variable. The selected characteristics are selected based on the research by Adrian and Brunnermeier.

5-5-1. Lagrange Multiple Test

In this section, through Lagrange multiple test, this hypothesis will be checked whether it is possible to use the panel data method to examine the association between the introduced metrics and systemic risk. Hypotheses H_0 and H_1 are defined as below:

H_0: The effects are not significant.

H_1: The effects are significant.
Based on the R software, the outputs of the Lagrange test are as follows:
Lagrange Multiplier Test - two-ways effects (Honda) for balanced panels
Data: dcc_DCoVaR ~ TE.TA + log.Cap + CA.TA
Normal = ٩,٣١٨٩, p-value < ٢,٢e-١٦
Alternative hypothesis: significant effects

Since the P-Value is less than 5% (2.2 to the negative power of 16) at the 95% confidence level, and on the other hand, the null hypothesis is rejected (the effects are not significant) according to the output of the model, the alternative hypothesis that is the significance of effects is confirmed. In summary, the above test's results confirm that the panel data method may be employed at a confidence level of 95%.

5-5-2. F-Limer Test (Chow)

In the case of combined[10] data, initially the F-test (Chow) is carried out to select the model estimation method between the two Pooling and Panel methods.
H_0: The intercepts are equal in all sections (Pool data)
H_1: The intercepts are not equal in all sections (Panel data)
F test for individual effects
Data: dcc_DCoVaR ~ TE.TA + log.Cap + CA.TA
F = ٩,٧٥٤, df ١= ٦, df ٢= ١٣٠, p-value = ٧,٣٣٢e-١٠
Alternative hypothesis: significant effects
At the confidence level of 95%, the P-value is less than 5% (7.3 to the negative power of 10), the H_0 hypothesis is rejected, and the alternative hypothesis is confirmed.

5-5-3. Hausman Test

In case that H_0 hypothesis is rejected after F-Limer test, the question is raised that in which form of fixed or random effects the model should be estimated. In Hausman test, the hypotheses H_0 and H_1 are defined as follows:
H_0: Random effect model
H_1: Fixed effect model
Hausman Test
Data: dcc_DCoVaR ~ TE.TA + log.Cap + CA.TA
Chisq = ٣٠,٩٦٧, df = ٣, p-value = ٨,٦٣٧e-٧
At the confidence level of 95%, the P-value is less than 5% (p-value = ۸/۶۳۷e-۷); the hypothesis H_0 is thus rejected. Hence, the fixed effect model should be employed in the DCC model.

5-5-4. Panel data regression model for investigating the association between systemic risk and bank characteristics

The regression model for investigating the association between systemic risk and bank characteristics is presented below:

$$\text{DeltaCoVar}_{it} = \alpha_i + \beta_1 \left(TE/_{TA}\right) + \beta_2 \left(Log\ Cap\right) + \beta_3 \left(CA/_{TA}\right) + \varepsilon_{it}$$

Based on the table above and according to the model's output, only the capital growth has a P-Value less than 5%. Therefore, capital growth is in an inverse and significant relationship with systemic risk. In other words, increased capital in banks and improved CAR will decrease the systemic risk in the market.

Table 6: The estimation results of panel data regression model based on the calculated systemic risk

P-Value	t statistic	Coefficient	Variables description	
0.9419	0.0731	0.01228	Leverage ratio	TE/TA
0.0006	-6.0017	-0.0773	Capital growth	Log Cap
0.1453	-1.4653	-0.1094	The ratio of cash assets to total assets	CA/TA

6. Conclusion and Suggestions

Given the results, systemic risk can be explained by the development of changing the CoVaR (the answer to the research's main question). The present study's result is consistent with that of Adrian and Brunnermeier (2016). They investigated systemic risk measurement with ΔCoVaR approach. For the first hypothesis (the banking sector's high dependence on the capital market), the two concepts of correlation (unconditional and conditional) were used. The model's outputs confirm the first hypothesis. In the next section, systemic risk measurement models were presented in the form of the main approach of DCC-t Student-MGARCH to calculate Delta CoVaR (systemic risk measure). We showed the better fit of ΔCoVaR for systemic risk than VaR and CoVaR models; in other words, at the banking network level, systemic risk measurement works better than individually measuring each bank. The investigated banks were ranked with the help of the two RMSE and

[10] Or hybrid?

MAE measures of systemic risk. The last part investigated the third hypothesis (the presence of a relationship between systemic risk and banking characteristics). In this section, while introducing three characteristics of 1- Leverage ratio, 2- Size (logarithm of capital) and 3- Ratio of cash assets to total assets, the use of panel data method was confirmed using Lagrange Multiplier (LM) test. In addition, with the help of F-Limer test (Chow), it was determined that the data is of panel type. Subsequently, according to the Hausman test, the fixed effect method was determined to be appropriate for the DCC model. The third hypothesis' output confirmed the inverse and significant relationship of the capital growth with systemic risk (in other words, improving banks' CAR significantly reduces systemic risk). Other findings of the study indicated that the traditional look at the issue of risk and risk-based legislation of a bank in isolation (i.e., considering the risk of a bank just with itself) would lead to additional risk-taking along the systemic risk dimensions. Furthermore, the identical parametric measures of risk (such as VaR) would not result in the existence of identical ΔCoVaRs as a systemic risk measure.

The result of the present study is in line with the result of Adrien and Brunnermayer (2016). They have studied comprehensive risk measurement with conditional value at risk (ΔCovaR) approach. Also, another part of the current research, that the equality of parametric risk criteria (such as VaR) does not lead to the existence of equal ΔCoVaRs as a measure of Systemic risk, is consistent with the results of Adrien and Brunermeyer's research. Also, another finding of the research states that conditional correlation increases during financial crises and at the same time as conditional correlation decreases, the stock price of the banking sector has increased significantly. Another finding of the research is consistent with the findings of Abrishmi et al.'s research (2018), which states that Systemic risk is not only directed at large banks, but small banks also play a role in the emergence and spread of this risk. Also, another finding of the research based on the application of the DCC-t student-MGARCH model to explain Systemic risk is consistent with the findings of the research of Jabal Ameli and others (2019). According to the current research, the systemic dependence of the whole market on the banking sector is high. The criterion of dependence in this research is conditional and unconditional correlation, and in the unconditional criterion, the dependence rate is about 70%. This finding is consistent with the research of Rostgar and Karimi (2015).

Accordingly, the suggestions below are presented:

1) As the highest authority for monetary policy, The Central Bank is recommended to periodically measure the banking system's systemic risk, identify the systemically important banks, and announce policy measures to restore these banks' balance sheet structure. To this end, it is of paramount importance to use suitable models to forecast systemic risk.
2) Based on the previous paragraph, taking measures to identify and control systemic risk should be separately investigated in temporal and cross-sectional dimensions. In temporal dimension, early-warning indicators of financial distress are required, while in the cross-sectional dimension, each institution's quantitative share in the systemic risk must be determined.
3) Higher loss absorbency (HLA) requirements should be specified for banks with important systemic risk to be responsible for the greater risk created by their failure for the country's financial system. For instance, in Basel III, SIFIs (systemically important financial institutions) are obliged to save additional capital commensurate with the systemic importance of the financial institution. The aforementioned requirements should be specified at both levels of the parent bank and its subsidiaries.

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