



# A quantitative measure of financial resilience of firms: Evidence from Tehran stock exchange

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Received 24 April 2020; received in revised form 15 November 2020; accepted 13 January 2021

## KEYWORDS

Financial crisis;  
 Financial resilience;  
 Financial risk;  
 Value at risk;  
 Tehran stock  
 exchange.

**Abstract.** Recent financial crises have strained the performance of different firms and understandably, investors have doubts about making serious investments in the stocks of shaky firms. Measuring the resilience of a firm from a financial standpoint in the face of crises is an important indicator for investors. Logically, investing in firms that have continued to maintain their historically stronger financial resilience is more attractive for investors. In the literature, resilience is defined as anticipating, preparing, responding, and adapting to incremental changes and sudden disruptions to survive and prosper. In this paper, the concept of financial resilience has been studied from various dimensions, and its quantification approaches are examined. The models developed in this paper are for calculating financial resilience in terms of key indicators: value at risk and conditional value at risk. Then, upon comparing these methods, an attempt is made to verify the performance of methods based on the quantitative data of four bankrupt and four non-bankrupt firms listed on the Tehran stock exchange in recent years. The results show the proper performance of the proposed measure in expressing the concept of financial resilience in critical conditions.

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## 1. Introduction

Investors are generally looking for profitable firms to invest in. One of the factors that may tempt investors, besides considering technical and fundamental analyses, to choose a stock is the historical performance of a firm in response to market shocks [1]. Naturally, all firms have experienced crises and risks at different times. In general, a risk is an event that affects the goals of an organization, either positively or negatively [2]. In one classification, the risks inherent in a business are divided into three categories as follows. The first

category includes risks that a firm has no control over and is only affected by them. The second category includes risks affected by the firm, but this impact is minor and mostly absorbed. The third category includes risks that affect the firm's financial aspects, but the firm has the tools at disposal to control those risks. For investors, however, this risk will emerge as a financial risk. Financial risk is the potential to face a financial loss and the uncertainty inherent in developing a capital [3]. Investors need to look at financial risk management tools to control this risk and consider different risk-return scenarios [4]. Financial risk management consists of identifying and measuring financial risk, analyzing and evaluating it, formulating financial risk control strategies, responding and executing processes, and monitoring and controlling.

Traditional financial risk management has a rigid structure based on knowledge, analysis, strategy formulation, execution, and control. A review of previ-

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ous studies shows that the financial risk management strategies and responses have, traditionally, had poor performance. This weakness results from disregard for considering the synergistic effects of risks on the network and their overlapping, unifying the whole risks, and integrating them [3]. The main focus of the financial risk management process is on identifying, measuring, responding, and controlling financial risks, as well as aspects of operational risk in this process. The overall financial risk management process does not measure the viability of an entity against external shocks and risks affecting a firm. In the global economic downturn experienced during 2007, it was observed that simply having a plan and running a program could not guarantee success and that the performance should be considered and measured, too. There must be an appropriate mechanism in place with the least effect on performance under varying financial performances.

Therefore, investors are looking for a concept that can express the firm's situation under crises with a simple and accurate measure. This concept has been developed in connection with 'resilience' as a keyword in the literature. The concept of resilience indicates the ability to measure the effectiveness of risk response plans practically and to show the strength of a business in the face of risks or shocks. Indeed, it refers to a system ability to return to the normal situation following a disturbance [5]. Concepts such as stability, robustness, fault tolerance, flexibility, reliability, survivability, and agility are commonly mentioned alongside resilience. These concepts are also found in the definition set by Walker, Holling, and Carpenter [6]. Based on their viewpoint, resilience is the capacity of a system to absorb the effects of a shock as well as to return to its normal level when changes occur while its functions, structure, institutions, and feedback persist. From a financial viewpoint, resilience is the ability of a financial institution to absorb short-term shocks, including financial shocks, i.e., exogenous changes and types of business risks, and to maintain performance through long-term economic changes [7].

According to Maurer [8], financial resilience has four aspects: consistency, redundancy, rapid recovery, and resource adequacy. A review of the articles in the field of resilience shows that as we get closer to recent years, many studies have attempted to provide an approach to calculating resilience. The concept of resilience has been considered in different areas. A review of the trends shows that although the number of article papers in various fields is on the rise, the concept of resilience by itself in different areas needs further attention. In addition, there is a lack of quantitative integrated approaches in most areas, hence the need for a precise measure to calculate financial resilience quantitatively. Since firms' financial performance is

reflected in the value of their stocks, a number of articles have used the market index to calculate resilience [9]. Drawing on the same subject matter in this paper, financial resilience has been calculated using firms' stock value. For this purpose, financial resilience is measured in three cases. In the first case, resilience implies the total reduction of financial performance from the beginning of the shock period. In this case, from the beginning of the stock devaluation to the end of this period, the total amount of this decrease is obtained. In the second case, financial resilience is generally calculated as the number of stock prices, which is below the Value-at-Risk of those stocks at a given time after the crisis. The concept of Value-at-Risk (VaR) was developed to determine the expected loss according to a predetermined confidence level. This concept makes it possible to warn an investor about the risk in the event of a loss in investment and to inform investors of necessary steps to take [10]. Since this value represents loss limit, this paper considers exceeding this point as a critical period of financial value, and financial resilience in the second model is considered accordingly. In the third case, the value of financial resilience is calculated using the conditional VaR concept, assuming that the cause of the crisis is identified and its effect on the system performance attenuation is calculated. In fact, the concept of Conditional Value at Risk (CoVaR) can be considered as VaR, with the exception that the share of external factors, which is the cause of a shock for financial performance, is considered as systemic risk in CoVaR [11]. In the third model presented in this paper, the cause of shock and its effect are considered, and financial resilience is calculated based on financial performance, which overpasses the CoVaR.

Given that there is no precise approach in the literature that can show the financial resilience of firms quantitatively in a certain period of time, this study develops a measure of financial performance based on five financial indicators: stock prices, Earnings Before Interest and Taxes (EBIT), the ratio of total liabilities to the total value of the company's assets, working capital on total assets, and Earnings Per Share (EPS). Therefore, as a contribution of this study, standard approaches of VaR-based (risk calculation) and CoVaR-based (systemic risk calculation) measures have been developed.

In the following sections, first, the background is presented. Next, a quantitative measure will be proposed and the available historical data will be used to validate the proposed measure. For this purpose, by analyzing the data of eight stocks listed on the Tehran Stock Exchange (TSE) from 2010 to 2018, firms' financial resiliency that has gone bankrupt in recent years is compared with others. Finally, different methods for calculating financial resilience are discussed.

## 2. Background

Financial resilience was first defined by McDonough in 2003. From his view, the concept of resilience is the unaccompanied means of controlling the costs of an institution in the face of rapid inflation at that time in the United States [7]. In the 2000s, financial resilience was first explored at the household level as an approach to controlling the financial crisis in a family. A number of other studies have also explored the financial resilience in the public sectors and economics of countries and referred to strategies for combating turbulence in economic factors including inflation, exchange rate, and macroeconomic parameters.

The year 2008 can be considered as a turning point in the financial resilience development research. The issue of resilience in the literature has been receiving much attention after the 2008 financial and economic crisis. The most important findings in this regard are summarized in Table 1.

A review of the literature in this area shows that economic resilience is a tool for controlling the risks affecting the macroeconomics of a country. On the other hand, financial resilience is the ability of a financial institution to control its relevant risks. Given that evaluating financial resilience depends on particular indicators, we examine the relevant indicators introduced in the literature. These indicators are mainly derived from qualitative recommendations on the resilience of financial institutions. It is important to consider these indicators when developing a quantitative measure for calculating and improving financial resilience. Some of these indicators are controllable by an institution, and some of them will merely result in the passive performance of the institution. In general, resiliency assessment methods can be divided into two groups: qualitative and quantitative. The qualitative group includes methods that evaluate the resilience of a system using qualitative information. This group consists of two categories of conceptual frameworks and quasi-quantitative indicators. Conceptual framework development methods use certain approaches to develop a framework based on questionnaires for determining resilience (refer to Alliance [12] on resilience of socio-environmental systems). Quasi-quantitative methods are usually employed to measure the resilience based on the quantification of a questionnaire outcome using fuzzy numbers or Likert scale (refer to the research of Galvin et al. [13] on social resilience). Other methods used in this area include developed logistic regression models and the degree of resilience classification for a financial institution. Another approach in this area is use of clustering algorithms to measure the financial resilience of a financial institution [14].

Quantitative methods include two groups: general resilience methods and structure-based modeling

methods. General resilience methods provide few tools at disposal to evaluate resilience by measuring the system performance regardless of its structure. General methods of financial resilience are approaches that do not inherently incorporate probability in computation; however, they include the system resilience triangle based on the recovery time and system performance degradation developed by Bruneau et al. [5] and Zobel [15]. The probabilistic methods represent another type of general quantitative methods. In these types of methods, resilience is calculated based on the probability of different levels of initial post-crisis system performance decline and the probability of different time intervals for recovery (refer to Chang and Shinozuka [16] for refining an electricity system).

Structure-based approaches examine how a system structure affects the system resilience for which the system behavior is studied and then, its characteristics are modeled and simulated. In fact, this approach aims to analyze the change of the system performance and evaluate its resilience (not the resilience calculation). The structure-based methods are divided into four groups: optimization models, simulation models, fuzzy logic models, and factor-based models. Optimization approaches develop mathematical models and analyze different scenarios on the system either decisively/fuzzily or randomly and seek to find the best strategy in terms of resiliency (refer to the papers of Sahebjamnia, Torabi, and Mansouri [17] and Rezaei Soufi, Torabi, and Sahebjamnia [18] for organizational resilience).

Simulation approaches are established based on developing a system subjected to different events and analyzing its resilience in terms of time and scenario (refer to Adjetey-Bahun et al. [19] about resilience of transport networks). Factor-based approaches also model these behaviors by testing the role of various factors in controlling the resilience of a system while designing an architecture for the performance of these factors and testing its performance in various scenarios.

The following remarks are of value following our literature review:

- ✓ Disregard for financial resilience while most research studies have focused on social, human, and organizational domains;
- ✓ Disregard for the concepts of financial risk in the development of business continuity management and crisis management systems in the area of financial resilience of organizations;
- ✓ The existence of many developed qualitative and descriptive approaches to financial resiliency while a few quantitative approaches can provide investors with more accurate decisions;
- ✓ A significant body of financial resiliency research

**Table 1.** The summary of the related literature.

References	Risk assessment aspects					Calculation aspects		Developing mechanism	Main outputs
	Disruptive risks	Market risks	Credit risks	Systemic risks	Liquidity risks	Quantitative	Qualitative		
Main outputs									
Baur and parker [20]							✓		Defining financial resilience with regard to government debt markets and making suggestions to improve.
Guettafi & Laib [21]							✓	SH	Evaluating the stability of a financial system with regard to two factors of financial resilience and transparency and the use of accounting variables in the qualitative evaluation of stability.
Papenfub et al. [22]	✓		✓	✓			✓	EA	Evaluating financial resilience in Germany and the role of government in economic crisis. Evaluation through empirical study with regard to cash availability and questionnaire development.
Barbara [23]	✓			✓			✓	EA	Evaluating financial resilience in Italy by theoretical sampling of Italian municipalities and study of their financial performance before and after the economic crisis. Investigating shock absorption, vulnerability, predictive capacity, and coping capacity as four aspects of resilience.
Korak et al. [24]	✓		✓		✓		✓	SA	Evaluating government financial resilience in the state of Michigan by sampling and studying their financial performance with respect to the shock absorption, forecasting, and coping capacity aspects.
Pal et al. [25]	✓		✓		✓		✓	EA	Assessing government financial resilience in Sweden by sampling the four largest municipalities and studying the reasons for financial performance stability in the aftermath of the economic crisis.
De Aquino et al. [26]	✓		✓		✓		✓	EA	Evaluating the financial resilience of municipalities in Brazil by examining four major municipalities in the country, studying economic resilience indicators to evaluate and assess shock absorption, vulnerability, predictive capacity, and coping capacity as four aspects of resilience.
Jansson [27]	✓		✓		✓		✓	EA	Evaluating financial resilience as one of the organizational resilience sectors in six Swedish companies and analysis of factors affecting financial resilience through an empirical study of companies with good, bad, and medium financial statuses.
BCBS-Basel III [28]	✓	✓	✓		✓		✓		Developing resilience with focus on two aspects of macroeconomic and intra-firm aspects and providing qualitative strategies to promote.
Hallegatte [29]	✓						✓		Focusing on the concept of economic resilience, considering the system's performance in the wake of a disruptive crisis. Proposing functions defined in organizational resilience literature as a function of calculating the resilience of an economy.

Note: In developing mechanism column SA is Statistical Analysis, EA is Empirical Analysis, and SH is Statistical Hypothesis.

**Table 1.** The summary of the related literature (continued).

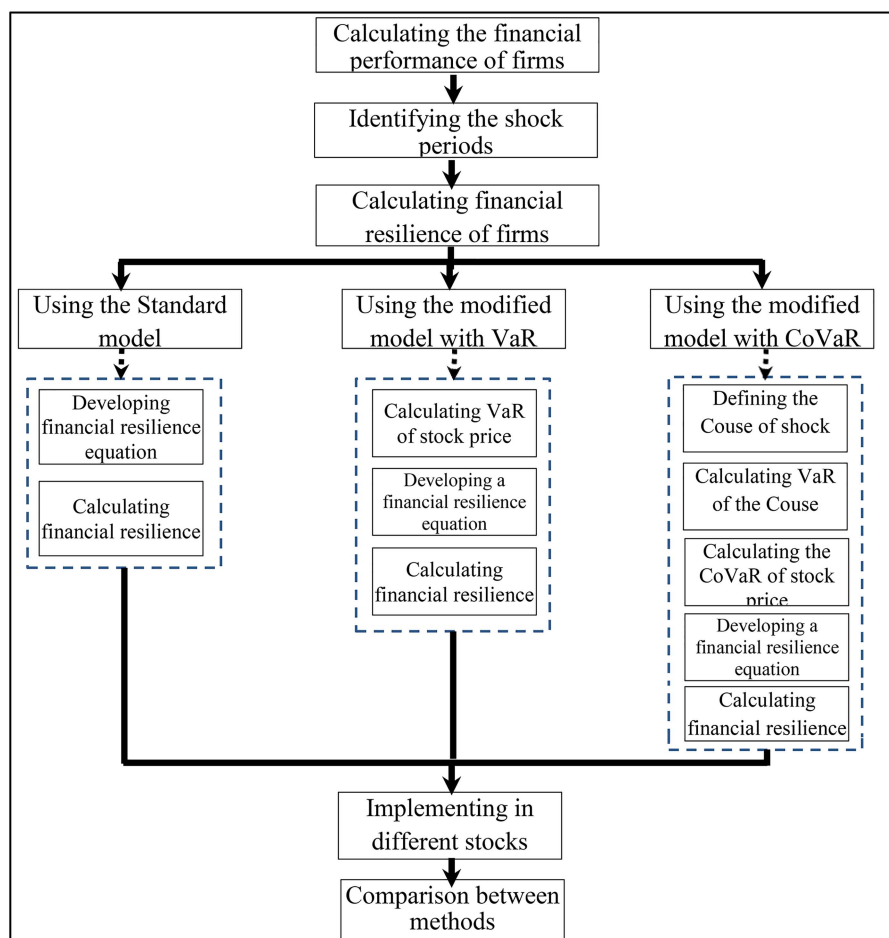
References	Risk assessment aspects						Calculation aspects		Developing mechanism	Main outputs
	Disruptive risks	Market risks	Credit risks	Systemic risks	Liquidity risks		Quantitative	Qualitative		
Pilgui [30]	✓	✓						✓	EA	Studying the impact of the global financial crisis on the Ukrainian banking system's financial resilience and suggest the basilar criteria to enhance the financial stability and resistance against crisis for banking systems.
Du Boys et al. [31]		✓						✓		Considering the vulnerability of local governments influenced by the global financial crisis. Finding that the local policies stem from macro-national policies and implementing resilience promotion policies in long-term and short-term programs can reduce the country's vulnerability to global crises. Not identifying the resilience promotion policies in detail.
Mirzaei and Al-Khouri [32]		✓					✓		SA	Analyzing Kuwait as an resilient oil-supplier economy in the global crisis and considering the banks and industrial growth situation. Industries dependent more on external finance have lower resilience during the global crisis.
Tabibian and Rezapour [33]	✓						✓		SA	Assessing the urban resilience and analyzing indicators in the assessment of urban resilience. Identifying 22 sub-criteria in 6 classes including social, economic, environmental, physical, infrastructural, and institutional ones for urban resilience.
Triggs et al. [34]		✓		✓	✓	✓	✓		EA	A survey of the crisis management experience in Indonesia in the crisis of Taper Tantrum 2013 which, despite the existence of risk, has a good performance in maintaining the unemployment rate, the positive trend of the capital market, and fixing the inflation.
Behl et al. [35]	✓						✓		SH	Studying the effect of natural disasters on financial sectors in India and finding that e-governance can improve the financial resilience.
Nkundabanyanga et al. [36]	✓	✓					✓		SH	Examining the relationship among firm characteristics, innovation, financial resilience, and survival of financial institutions in Uganda. Finding that firm characteristics such as size, age, innovation, and financial resilience have a predictive force on the survival of public interest firms such as financial institutions.
Salignac et al. [37]			✓					✓	EA	Defining financial resilience and developing a framework to measure financial resilience in Australia. Identifying economic resources, financial resources, financial knowledge and behavior, and social capital as financial resilience components.

Note: In developing mechanism column SA is Statistical Analysis, EA is Empirical Analysis, and SH is Statistical Hypothesis.

**Table 1.** The summary of the related literature (continued).

References	Risk assessment aspects					Calculation aspects		Main outputs
	Disruptive risks	Market risks	Credit risks	Systemic risks	Liquidity risks	Quantitative	Qualitative	
Klapper and Lusardi [38]		✓	✓		✓		✓	EA
Investigating the effect of financial awareness on the individual or organizational levels in promoting financial resilience and statistical analysis of the situation of people with different levels of financial knowledge in four areas of interest, credit instruments, asset distribution, and inflation in financial resilience viewpoint.								

Note: In developing mechanism column SA is Statistical Analysis, EA is Empirical Analysis, and SH is Statistical Hypothesis.

**Figure 1.** The flowchart of the proposed approach.

using descriptive approaches that examined existing examples and experiences; financial institution managers need effective procedures to promote prescriptive financial resilience.

### 3. Methodology

This section proposes a quantitative measure to calculate the financial resilience of firms. Figure 1 shows the

flowchart of the proposed methodology. The details of each step are given.

#### 3.1. Measuring financial performance

Determining an appropriate function to measure the financial performance of a firm is one of the most important steps taken as part of our proposed approach implementation.

In order to determine an appropriate measure of

financial performance in this paper, a set of financial indices is used, as reported in the periodic reports of firms. These indices are identified by examining the literature on the indices available in the financial insolvency review. Notably, the indices with maximum available data are selected. These measures are stock prices [39], EBIT [40], the ratio of total liabilities to the total value of the company's assets [41], working capital on total assets [42], and EPS [43]. In order to integrate the metrics and create a function for each firm, the highest and lowest numbers at a specific time are identified, and the numbers at each time are normalized. Then, the integrated value is obtained by considering the positive or negative nature of each measure in determining the financial performance, the weight of each measure obtained by the Shannon entropy method, and using the simple weighted sum method. The Shannon entropy method is presented as follows.

For a component  $X_i$  with  $M_X$  possible states, each having a corresponding probability of  $p(x_i)$ , the average amount of information gained from the component measurement ( $x_i = x_1, \dots, x_{Ma}$ ) is defined by the Shannon entropy ( $w_i$ ) [44] as follows:

$$w_i = -\sum p(x_i) \log p(x_i) \quad \text{in each time period.} \quad (1)$$

Accordingly, the weighted sum formula is as follows:

$$A_j^{WSM-Score} = \sum w_i a_{ij} \quad \text{in each time period,} \quad (2)$$

where  $w_i$  is the weight of each financial index  $i$  (calculated based on Eq. (1)), and  $a_{ij}$  is the normalized value of financial performance index  $i$  for firm  $j$  in each time period.

### 3.2. Calculating the shock periods

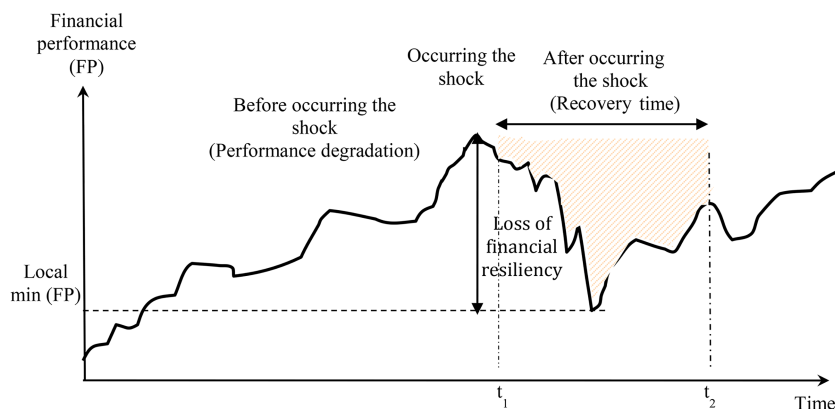
The second step to measure the resilience is to determine the shock periods. For this purpose, by calculating the financial performance function and drawing the financial performance status chart in a time period, the periods of change in the financial situation trend will

be examined. When a trend is reversed and becomes negative amid increasing or stabilizing financial performance, financial distress begins. In addition, when a trend is positive and begins after a negative trend period, the period of financial distress ends. In fact, this section is the main difference between calculating financial resilience and organizational resilience that has already been developed in the literature. In the case of organizational resilience, the performance rate is usually constant (for example, the production capacity of 1 million units per day) and reaches a lower level after the crisis. At the end of this period, the amount of performance returns to the previous level or exceeds. This value may never return to the previous value in financial performance, although experiencing positive trend patterns with a lower slope. For this purpose, the trend-changing pattern has been used in this paper to determine shock periods.

### 3.3. Calculating the financial resilience

The proposed measure of financial resilience should distinguish between good and bad firms based on their financial performance and define the impact of shocks on firms. Therefore, it should have either a bad time period (disaster period) or a good time period (the time that the firm does not face any particular crisis). Since a firm's financial resilience should be reflected in its balance sheet and based on the literature review, the measure should be designed to include balance sheet information. The financial resilience measure must be designed applicable to any financial institutions, and with minor modifications, it could be used to calculate the financial resilience of other firms. Figure 2 presents a general diagram of the measure designed in this paper. According to Figure 2, it can be seen that the financial performance of a firm reduces dramatically after the shock. A firm is resilient if it sustains less damage when experiencing a shock (performance degradation) and if it returns to the normal condition rapidly (resuming time).

Given these two concepts (performance degrada-



**Figure 2.** The main model of financial resilience measurement.

tion and resuming time), the following function as the basic Loss of Financial Resiliency (LoFR) model has the ability to integrate these values with both parameters and express them as a loss of financial resilience.

Loss of Financial Resiliency (LOFR) =

$$\int_{t_1}^{t_2} f(FP)dt - \text{Local min}(FP) \times (t_2 - t_1). \quad (3)$$

Note that in Eq. (3),  $f(FP)$  denotes the performance of the firm at different times; Local min ( $FP$ ) is the minimum of performance following the crisis,  $t_1$  is the time of performance degradation after a positive trend, and  $t_2$  is the time that the firms start to recover after the shock and the performance is reversed after a negative trend. According to Figure 2, the highlighted yellow area is the total LOFR. This area is associated with two variables of recovery time and the reduced level of financial performance. The recovery time is the time between the occurrence of a shock and the recovery of a firm's financial performance to its baseline level. Therefore, the lower level of financial performance reduction and the shorter recovery time yield higher financial resilience. Furthermore, we can see that a set of geometric shapes can fit the performance reduction area, such as a combination of triangles and trapezium in Figure 3. This performance reduction area can be used as a good approximation

for the estimation of the LOFR. Therefore, in the rest of this study, the approximate approach is employed to measure the financial resilience.

The second model employed for measuring the LOFR is based on VaR of financial performance.

In the previous section, VaR is employed to measure the investment of loss limit. In fact, crossing this level indicates entry into the critical range of losses based on a predetermined confidence level. In this section, the amount of financial resilience is calculated using VaR as a critical threshold. Notably, there have been a variety of approaches to computing VaR, and various supplements have been developed for it. However, this paper uses a simple type using historical data to calculate it. The modified model for different risks is as follows. The relevant function is presented in Eq. (4). Similar to the basic LOFR model, the approximate models can be applied here.

$$LOFR = \int_{t_1}^{t_2} f(FP(t)|FP < VaR^{FP})dt. \quad (4)$$

Notably,  $t_1$  is the time when the financial performance level goes from a higher value to a lower value compared to the VaR, and  $t_2$  is the time when the financial performance level goes from a lower value to a higher value compared to the VaR. According to Eq. (4), the level of financial performance, which is below VaR level, will be effective in measuring financial resilience (see Figure 4).

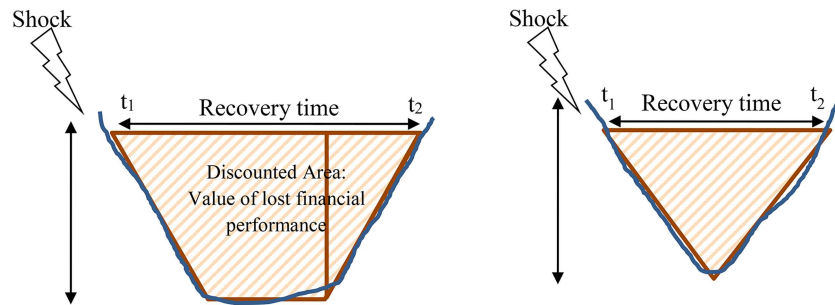


Figure 3. A schematic view of the modified LOFR (Loss Of Financial Resiliency).

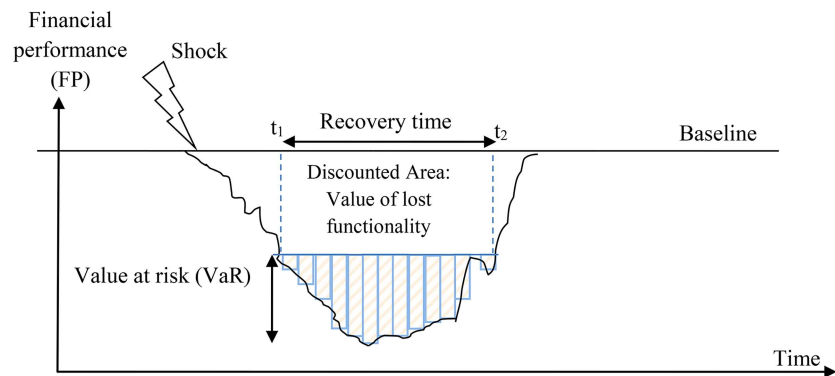
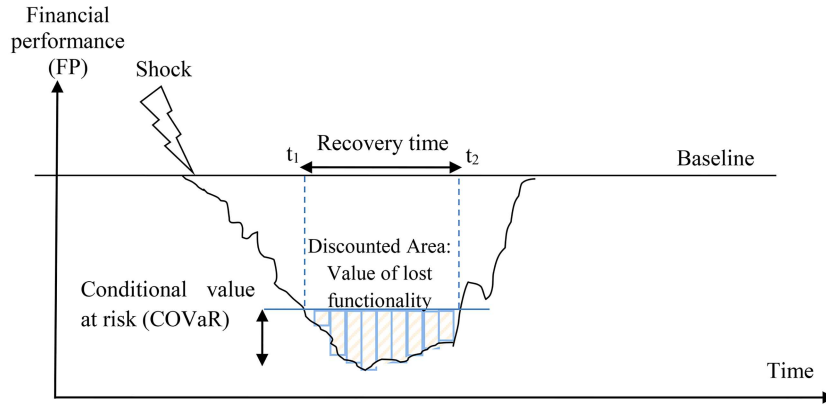


Figure 4. A schematic view of LOFR (Loss Of Financial Resiliency) function for different risks.



**Figure 5.** A schematic view of LOFR (Loss Of Financial Resilience) function for systemic risks.

The next model is the modified LOFR involving particular risks in the market. In this respect, the CoVaR of functionality is used. At this phase, the cause of the shock is identified which is considered as a systemic risk (see Figure 5).

CoVaR can be considered one of the approaches related to VaR. In this measure, the contribution of an external factor to creating the shock is measured and the new value of the VaR is calculated. The issue of the external event, which is generating a shock against a system, remains in the systemic risk literature, and CoVaR is one of the measures used to calculate the systemic risk. There have been various approaches to calculating CoVaR in the literature, all of which have been developed based on correlation given the need to measure the contribution of external factors and the corresponding effect on the main variable of the study.

To consider the systemic risk, this study uses CoVaR measure, as given in the work of Girardi and Ergün [45], to investigate the fluctuation effects of shock variable on the capital markets of the Middle-Eastern countries. For this purpose, assume that  $x_t$  is the financial performance indicator at time  $t$ , and  $x_t^o$  is the return of systemic risk affecting the financial performance at time  $t$ . Accordingly, the CoVaR measure at a  $(1 - \beta)$  level of confidence can be calculated below based on the  $\beta$ th percentile of the conditional distribution of  $x_t^f$ :

$$\Pr(x_t^f \leq CoVaR_{\beta,t}^f | x_t^o \leq VaR_{\alpha,t}^o) = \beta. \quad (5)$$

In this equation, the expression  $VaR_{\alpha,t}^o$  shows the VaR variable that affects the system and represents the maximum loss experienced in this market at a  $1 - \alpha\%$  level of confidence at time  $t$ . Using conditional distribution rules, we will have:

$$\Pr(x_t^f \leq CoVaR_{\beta,t}^f | x_t^o \leq VaR_{\alpha,t}^o) = \alpha\beta. \quad (6)$$

With these explanations, the loss of resilience for this model is given in Eq. (7):

$$LOFR = \int_{t_1}^{t_2} f(FP(t) | FP < CoVaR_{Systemic Risk}^{FP}) dt, \quad (7)$$

where  $t_1$  is the time when the financial performance level declines from a higher value to a lower value than the CoVaR, and  $t_2$  is the opposite trend.

In the next sections, the proposed three approaches are applied to the case of eight firms and then, their capability is compared. Furthermore, the efficiency of the approaches in distinguishing between companies with good and bad financial performances is compared with that of Altman Z-score model [46].

Altman Z-score model is able to predict the bankruptcy of the understudied firms. This model considers five financial ratios as working capital/total assets ( $A_1$ ), retained earnings/total assets ( $A_2$ ), earnings before interest and taxes/total assets ( $A_3$ ), the market value of equity/total liabilities ( $A_4$ ), and sales/total assets ( $A_5$ ), and develops a linear weighted sum model as:

$$Z\text{-score} = 1.2A_1 + 1.4A_2 + 3.3A_3 + 0.6A_4 + 0.999A_5.$$

When the value of the linear model is higher than 2.99, the firms are in the safe zone; when the value is lower than 2.99 and higher than 1.81, the firm is in the gray zone; and when the value is lower than 1.81, the firm is in the distress zone.

#### 4. Data and results

In order to evaluate the ability of the proposed models and validate them in this section, the data belonging to eight firms listed on the TSE are used. Four of these firms had a good financial performance during 2010-2018, and the other four firms were in bankruptcy. Table 2 shows the list, industry groups, and relevant disruption periods of these firms.

Given the lack of transparency regarding the definition of bankruptcy in the Iranian market, the following definitions are utilized to distinguish between bankrupt and non-bankrupt firms:

**Table 2.** The list of firms and relevant information.

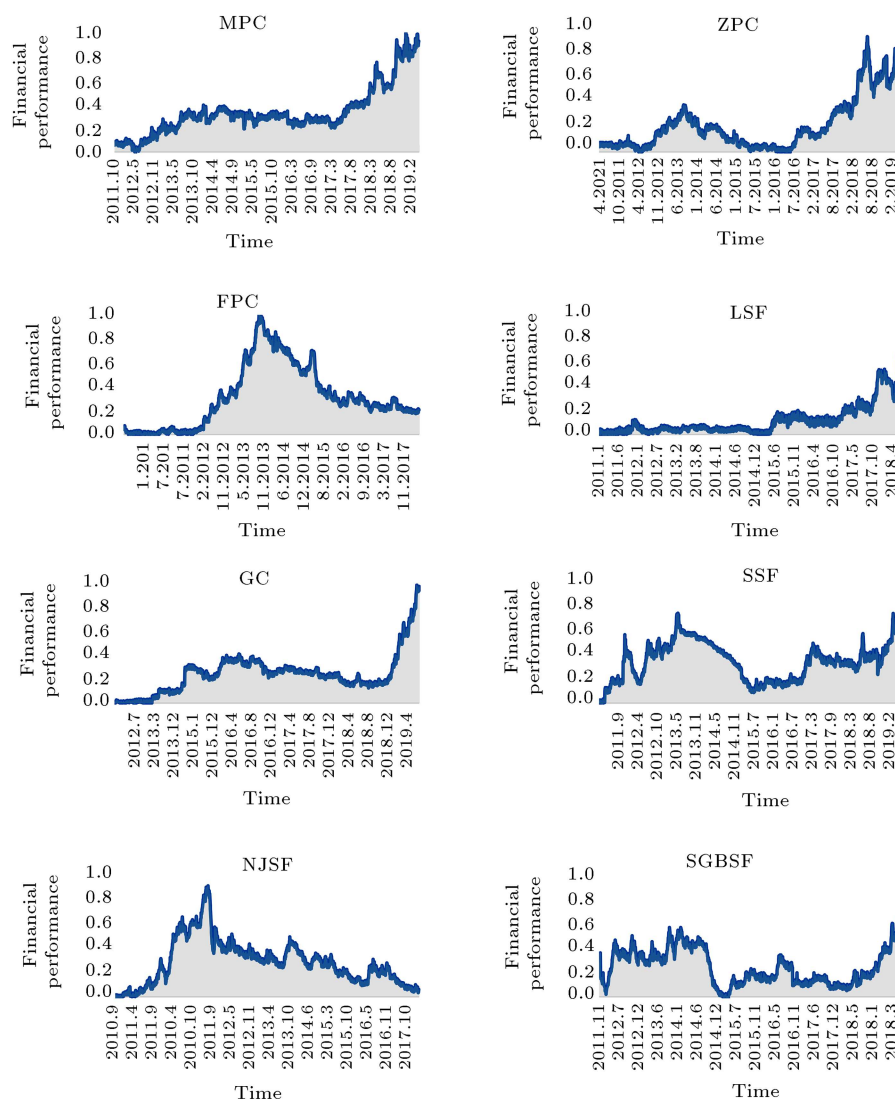
Firm	Period of disruption	Industry group	Bankrupt	Description
Marun Petrochemical Company (MPC)	9.2018-3.2019	Petrochemical		The company has not accumulated losses in any year.
Zagros Petrochemical Company (ZPC)	1.2014-6.2014 9.2018-2.2019	Petrochemical		The company has not accumulated losses in any year.
Glucosan Company (GC)	10.2016–6.2017	Foodstuffs		The company has not accumulated losses in any year.
Lorestan Sugar Factory (LSF)	1.2014–9.2014	Foodstuffs		The company has not accumulated losses in any year.
Farabi Petrochemical Company (FPC)	5.2018–9.2018	Petrochemical	✓	The company had accumulated losses in the three years 2015–2017, and its accumulated loss ratio to the amount of capital was more than eight times.
Shirin Sugar Factory (SSF)	3.2014–1.2015	Foodstuffs	✓	The company had accumulated losses from 2016 to 2019, and its ratio of accumulated losses to the amount of capital has been more than four times.
Naghshe Jahan Sugar Factory (NJSF)	9.2015-6.2016 12.2017–6.2018	Foodstuffs	✓	The company had accumulated losses from 2016 to 2019. Its ratio of accumulated losses to the amount of capital has more than two times.
Shirvan-Ghoocahn-Bojnourd Sugar Factory (SGBSF)	9.2014–9.2015	Foodstuffs	✓	The company had accumulated losses in the five years 2014–2018 and its accumulated loss ratio to the amount of capital was more than 1.5 times.

- Bankrupt: Firms with accumulated losses in accordance with Article 141 of Commercial Code of Iran during 2010–2018;
- Non-bankruptcies: Firms that made profits in the period of 2010 to 2018.

Through the application of the proposed approach to generating the financial performance of each firm in Section 2, the available data are used and the financial

performance charts of eight understudied firms calculated. These financial performance charts are presented in Figure 6 as the required steps to determine financial resilience. According to these figures, the periods of disruption are identified.

All the data sets are gathered from the TSE website on a monthly basis. Furthermore, given that the financial data of companies are not reported in short periods, it is not possible to collect data in



**Figure 6.** The financial performance of different firms.

periods shorter than a month. Short time periods (e.g., daily) are so small that they will not illustrate a shock effect due to high fluctuation.

The results of the first model application (standard LOFR model) are presented in the second column of Table 3. The results demonstrate that the application of this method is capable of separating firms with good and bad performances (bankrupted).

In the second model (VaR-based), there is a need to calculate VaR for each firm. Therefore, maximum data are used to calculate it. In this approach, the degree to which the firm's conditions are lower than the value at risk is used. As demonstrated by the study results, firms that maintain a longer distance from their VaR in a more time-consuming manner are more likely to go bankrupt and are less resilient. Results are presented in the third column of Table 3.

Of note, in order to calculate the VaR, historical simulation models are used and all confidence levels

are set at 95%. The results of VaR are prepared in the third column of Table 3.

Finally, for the third model (CoVaR-based), a detailed study was conducted to identify the causes of the shocks. It was found that more than 20% fall in oil and gas condensate prices in October of 2018 for petrochemical firms and the change in the price of raw materials for food staff firms were the main reasons for this devaluation. By calculating the VaR of oil and sugar prices, the CoVaR of financial performance of each of the eight firms was calculated and the new resilience value was calculated. The fourth column of Table 3 shows the resilience values for the third method and other required information.

It is important to note that for firms with more than one period of a financial shock, the average financial resilience in these periods is considered.

According to Table 3, calculating financial resilience in the standard model has a lower value

**Table 3.** The results of different models of financial resilience calculation.

Firm	Standard method Average of LOFR	VaR-based method		CoVaR-based method		
		VaR (95% confidence level)	Average of LOFR	The cause of risk	CoVaR (95% confidence level)	Average of LOFR
Marun Petrochemical Company (MPC)	0.2648	0.443	0.1962	Change in the price of oil and methanol	0.418	0.1886
Zagros Petrochemical Company (ZPC)	0.3266	0.122 (period 1) 0.446 (period 2)	0.2707	Change in the price of oil and methanol	0.098 (period 1) 0.411 (period 2)	0.2685
Glucosan Company (GC)	0.2963	0.264	0.2243	Change in raw material price	0.231	0.2049
Lorestan Sugar Factory (LSF)	0.1743	0.065	0.1591	Change in raw material price	0.053	0.1433
Farabi Petrochemical Company (FPC)	0.5342	0.193	0.3984	Change in the price of oil and methanol	0.144	0.3612
Shirin Sugar Factory (SSF)	0.6914	0.187	0.5712	Change in raw material price	0.129	0.5563
Naghshe Jahan Sugar Factory (NJSF)	0.6104	0.133 (period 1) 0.073 (period 2)	0.5246	Change in raw material price	0.098 (period 1) 0.046 (period 2)	0.4958
Shirvan- Ghoocahn-Bojnourd Sugar Factory (SGBSF)	0.7431	0.046	0.6311	Change in raw material price	0.018	0.6038

than the VaR- and CoVaR-based models. Resilience in the first model involves the total amount of lost performance and reduced efficiency. In the second and third models, however, the attenuation of performance occurs only at values less than VaR or CoVaR threshold, which in turn will result in lower resilience. Moreover, in the third approach, the use of an effective factor in reducing financial performance to some extent modifies the calculations. In fact, if we reduce the effect of this shock, which acts as a systemic risk, a new value will be obtained by determining the risk factor and calculating its effect on the stock price. Table 3 reveals that the scope of resilience loss is reduced by identifying the causes of a shock. Of course, this is particularly true for bankrupt firms.

## 5. Discussion

In this paper, three different quantitative methods were developed for measuring the financial resilience

of firms. The standard method considers the financial performance of firms and calculates financial resilience after reducing financial performance. The second method defines the VaR and calculates financial resilience. The third method considers the origin of the risk factor and uses the CoVaR concept to calculate financial resilience.

In the primary resilience approach defined in the engineering sciences, this concept is calculated by considering any deviation from the normal functional level. The same definition is used in the standard model of financial resilience, and the amount of resilience is calculated based on the deviation from the performance level in the pre-crisis state. In this situation, the concept of resilience is easily understood by senior managers. However, in the financial risk literature, risk metrics are often used and financial managers have a better understanding of these issues. For this purpose, the concepts of VaR and CoVaR have been employed. In order to investigate one more factor

**Table 4.** The strength and weaknesses of different models for financial resiliency calculation.

Method	Strength	Weakness
Standard model	Very simple and understandable; close to the traditional concept of resilience	Relatively low accuracy; disregarding the cause of the crisis
Modified VaR based model	Relatively simple and understandable; high accuracy	Need relatively large data; disregarding the cause of the crisis
Modified CoVaR based model	High accuracy regarding the cause of the crisis	Needs lots of data; complex and time-consuming; far from the traditional concept of financial resilience

**Table 5.** The comparison between different methods.

Firm	Z-score	1st FR model	2nd FR model	3rd FR model	Bankrupt
MPC	3.23 (*)	0.7352	0.8038	0.8114	
ZPC	2.25 (**)	0.6734	0.7293	0.7315	
GC	2.74 (**)	0.7037	0.7757	0.7951	
LSF	3.59 (*)	0.8257	0.8409	0.8567	
FPC	1.97 (**)	0.4658	0.6016	0.6388	✓
SSF	1.67 (***)	0.3086	0.4288	0.4437	✓
NJSF	1.52 (***)	0.3896	0.4754	0.5042	✓
SGBSF	1.04 (***)	0.2569	0.3689	0.3962	✓

Note. \*: The Z-score in the safe zone; \*\*: the Z-score in the grey zone; and \*\*\*: the Z-score in distress zone.

(such as the type of risk affected), the use of VaR and CoVaR methods is more accurate and useful for the organization managers. There are better plans for improving their resilience in the future by examining various factors and their performance in the past. Of course, investors and managers of financial institutions may not find this extent of review valuable given the need for a large amount of data. Here, the strengths and weaknesses of each method are considered, as shown in Table 4.

It is worth noting that all the three groups of managers of financial institutions, micro-investors, and the financial managers of organizations can use the financial resilience measurement approaches. The first two groups involve past and current financial resilience of companies and use this criterion along with other criteria to buy stocks. In comparison, the financial managers of organizations should take measures to get out of the current situation by examining the risk factors and comparing the situation with the group shares during the risk, which is not within the scope of this study.

Our results concerning the performance of three methods indicate the viability of the proposed methods.

Herein, the Altman Z-score model is applied to

comparatively evaluate the capability of the proposed model to predict the bankruptcy of the understudied firms. The results are shown in Table 5. According to this table, in the case of firms with no bankruptcy, the Z-score is in a safe zone and financial resilience holds a significant distance from the financial resilience of bankrupt companies. For firms that have already experienced bankruptcy, the Z-score is in the distress zone and the calculated financial resilience value significantly varies from that in non-bankrupt firms. Nevertheless, for firms within the grey zone of the Z-score model, one firm is bankrupt, while two other firms have not gone bankrupt. Moreover, the Z-score cannot determine the status of these firms; the calculated financial resilience has a good ability to separate the bankrupt from non-bankrupt firms. Therefore, our proposed method exhibits a good performance in separating between the two mentioned types of firms.

## 6. Conclusion

Financial fluctuations, changes in commodity prices, and economic crises cause financial damage to firms. In this regard, the issue of financial resilience of firms, especially after the economic crisis of 2008, was considered. Most studies in this field were limited to qualita-

tive recommendations on improving resilience, statistical models for developing hypotheses, and regression models to examine resiliency. The existing quantitative methods have usually divided the firms into good and bad groups by classifying financial resilience. In fact, the lack of a precise method that can indicate the financial resilience of firms in small steps of time has been one of the problems. In this paper, the resilience status of firms was investigated based on the financial performance. For this purpose, a function indicating financial performance was developed using stock prices, Earnings Before Interest and Taxes (EBIT), ratio of total liabilities to the total value of the company's assets, working capital on total assets, and Earning Per Share (EPS). Then, according to the financial performance chart, the shock periods were identified. By developing the lack of resilience as a function, which was measured based on the loss of performance during the shock period, the financial resilience value was calculated. This paper developed three models to calculate the financial resilience in standard, Value-at-Risk (VaR)-based, and Conditional Value-at-Risk (CoVaR)-based models. In the first case, the total lost performance was considered. In the second case, the loss of performance was considered for the area below the VaR value. In the third case, the loss of performance was determined for the area below the CoVaR value.

Notably, in the second and third approaches, the VaR of the financial performance should be calculated once with and without considering the risk causes. In this case, the financial performance function must be calculated by identifying the cause of a risk and calculating it.

In order to evaluate the performance of the proposed approach, the information of eight firms listed on the Tehran Stock Exchange was used. Among them, four firms have gone bankrupt (considered in accordance with Article 141 of Commercial Code of Iran), and four firms have been in a good position. Due to the need to identify the causes of the crisis in the three proposed methods to measure financial resilience, the eight selected firms belonged to two industrial groups: petrochemical and food staff.

The study of the financial performance of these firms revealed that there were several shocking periods for all of them. By identifying these periods, the resilience value was calculated in all the three methods. The results show a significant difference in the financial resilience value of bankrupt and non-bankrupt firms. However, even with the use of the Altman Z-score model, this separation was not well done.

It is recommended that future studies will provide a suitable mechanism for evaluating each of the qualitative approaches proposed in previous studies using the proposed financial resilience approaches. In general,

given the particular nature of this research, it was impossible to compare the three proposed approaches with those given in previous studies. The objective was to provide a method capable of measuring a company's resilience based on its past record as a measure of its financial performance from investors' perspectives. Moreover, future studies can focus on developing a different mechanism for integrating measures to define financial performance. They can use other different approaches to calculate VaR and CoVaR values (parametric and non-parametric approaches) and examine the differences in methods. Moreover, the research studies can identify the financial resilience status of each firm based on the balance sheet information forecasting approaches and use it as one criterion for investing in the firms.

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