Quantitative Analysis of Stock Market Resilience during Oil Price Shocks: Evidence from seven Middle East Countries

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Abstract

This study develops a quantitative approach to evaluate the resilience of stock markets of oil-supplying countries. To this point, the data from the stock market of seven Middle East countries are used, the shock periods are identified, an initial form of resilience is developed, and the performance of stock markets based on the oil price systemic risk is modified. Since during the disaster period, the pattern of changes in the financial markets is very important, a new approach to evaluate the amount of performance reduction after the disaster and recovering to the pre-disaster point is proposed. The proper performance of the proposed approach in showing the resilience of stock markets in different time steps has been evaluated quantitatively and qualitatively and the main policy of countries are reviewed. Our results indicate a positive and significant impact of the oil price shock on all stock markets, while the resilience of the best stock market is 20% higher than the worst market. Also, our introduced correction factor for the resilience measure has been able to provide a more realistic view of the resilience, as shown in the comparison of the resilience of countries and their economic indicators.

Keywords: Oil price shock, Stock market resilience, Systemic risk, Performance reduction, Recovery.

1. Introduction

The price of oil has fallen many times over the years, causing fluctuations in the stock markets in oil supplier countries and enshrouded the researchers to analyze their resilience assessment.

Resilience aims to strengthen a system by preventing system performance reduction and accelerating recovery to a pre-disaster state [1]. According to this definition resilience of stock markets can be considered an indicator that shows the impact of internal or external events on the stock market index and a stock market with a higher resilience has a lower tendency to be affected by shocks. A detail study of resilience should include the total impact of a shock comprising the severity of the system's performance reduction and the total duration of the system disruption [2]. The calculation of resilience in general conditions is usually through the area under the system performance curve during the recovery time period due to the occurrence of a shock (regardless of the type of accident) as shown in Figure 1-a [3]. As systems respond differently to various shocks, one of the challenges has been to examine the resilience in a specific event. Analysis of resilience after a particular shock can provide more accurate information for future experiences. So it is necessary to examine the shock due to a systemic risk such as oil price changes on the economic performance index separately. Figure 1-b attempts to separate the effect of a specific event from the total shock that occurred. In Figure 1-a, the total rate of performance reduction of the system (here the performance of the stock market) is examined, while in Figure 1-b, the exact amount of system performance reduction due to a specific shock (here, the shock of an oil price reduction) is considered. Another issue that is important is the difference between the period of decline of the performance index and the return of it which leads to different resilience values.

To this point, first, it needs to determine the effect of oil price shocks on the stock market using systemic risk measurement. Next, it requires evaluating the corresponding period in which the stock market was trapped in a disastrous event using resilience measures. Notably, the effect of each indirect disruptive factor on the market, such as oil price shock, is called a systemic risk [4]. The pertaining studies indicate that abrupt changes will increase the systemic risk of the system. Therefore, the systemic risk solely expresses an external shock's impact on the system.

Please insert Figure 1 about here.

Many studies show a strong correlation between oil prices and the growth rates of oil-exporting countries [5]. Indeed, the greatest damage from oil price changes occurs in the economies of Middle Eastern countries [6]. This study analyzes the stock market resilience of seven Middle East countries due to oil price shocks by applying our proposed methodology and tries to analyze the approach to risk reduction by improve resilience through examining the experience of countries. Therefore, we used stock market index data from Saudi Arabia, Oman, United Arab Emirates, Kuwait, Qatar, Bahrain, and Iran. These countries were chosen because they are the most important OPEC members, and OPEC+, with 70% of OPEC production capacity, are the most important producers and exporters of crude oil. Most of them also have a monopoly economy based on oil production and sales, and their macroeconomic conditions, including their stock markets highly dependent on oil price changes.

In this study, we calculate the resilience index of these countries and adjusting it in two stages by evaluating the direct impact of oil price shock and the performance of system in declining and recovering time periods.

The remaining parts of this paper has been organized as follows. Section 2 provides detailed literature review including main reseals of relevant studies as well as the research gaps and summary of the current research's contributions. Section 3 presents the research methodology including systemic risk calculation and our proposed method for measuring the resilience. Section 4 illustrates implementation of the proposed method including the data, calculations of systemic risk and stock market resilience. Section 5 discusses the stock markets' resilience during historical oil price shocks and provides the reasons for stock market resiliency. Finally, section 6 concludes the study and provides policy implications.

2. Literature Review

Analysis of stock market volatilities with the fluctuations in oil prices has a rich literature, however here we review researches relevant to Middle-East countries. Fayyad and Daly [7] contend that during the economic crisis of 2007, the increase in oil prices significantly affected the stock market indices in seven countries of Kuwait, Oman, UAE, Bahrain, Qatar, UK, and the USA. Arouri et al.[8] analyzed data from the Persian Gulf Cooperation Council countries between 2005-2010, applying a Value at risk (*VaR*)-*GARCH* method, and concluded that the world oil prices' fluctuations significantly affect the stock markets of the mentioned countries. Marashdeh [9] analyzes Saudi Arabia, the USA, and Russia using a vector error correction model to evaluate the oil price shock originated from the demand or supply side. Their results reveal the positive effect of oil price supply shock on Russia and the US stock market and the positive effect of oil price demand shock on all three countries.

In a study on the oil supply chain, Baig et al. [10] identified the most important oil supply and transportation risks and presented plans to improve its resilience. They identified crude oil price volatility, fuel price shocks, unpredictable demand, and information and communication disruptions as the most important operational risks in this field. They also identified real-time information sharing, traceability and transparency, and e-procurement as measures. Chatziantoniou et al. [11] studied the effect of upstream items' systemic risk on refined petroleum products. Using the Conditional Autoregressive *VaR* index, they concluded that there is a two-way positive relationship in this regard in major crises such as Covid-19 and the economic crisis. The systemic risk in their study is the risk of deviation from the baseline functionality of an index when an external event occurs. Different measures for calculating systemic risk have been defined in the literature. Acharya [12], for the first time, introduces a conceptual structure for determining the relationship between the risk of a bank and the changes resulting from the risk of the individuals having accounts in the bank. Adrian & Brunnermeier [13] introduce the conditional value at risk (*CoVaR*) as a measure for evaluating the effect of an exogenous event on an index indicating endogenous collective behavior. The other notable measures and models in the literature are average marginal loss [14], distance from the default [15], price of insurance against external financial distresses [16], Conditional Sharpe value [17], Extreme Value Theory [18], principal components analysis [19], default probability, and grid analysis [20].

Throughout recent years the *CoVaR* has been used as a suitable measure for calculating systemic risk. Note that the term "*Co*" in *CoVaR* combines four words: Contributing, Co-movement, Conditional, and Contagion [21]. It can provide information about *VaR* conditional on an external fact about another variable. In order to calculate the measure, it would be necessary to consider some conditions for distributing the data through copula functions. Brenchman and Joe [22] use a single-factor Copula with bivariate normal distribution for estimating the *CoVaR*. Mainik & Shaanning [23] use the Copula concept to calculate the *CoVaR* as a systemic risk measure. All measures provided in the literature are appropriate for analyzing the extent of a system's performance reduction due to an external disaster.

The main objective of our study is to consider the resilience of stock markets due to oil price shocks. Resilience is related to three concepts: Environmental adaptation (to prevent injury), shock resistance (for minimal post-shock performance reduction), and rapid recovery (to return to pre-shock condition) [24]. The amount of reduction in production from the normal level and the return time to the normal production level was considered by Bruneau et al. [25] and the integration of lost products based on these two concepts was seen as a loss of resilience by Zobel [26]. The concept of resilience in financial markets was precisely introduced in the last decade. Basel III defines resilience in financial viewpoint as a tool for strengthening regulatory capital frameworks and proposes a list of macroeconomic, accounting, and credit obligation rules to improve banks' resilience [27]. Due to the policy-making nature of the Basel Committee report, it was obvious that the technical aspects of calculating resilience were not presented in their study. Ovat [28] studies the resiliency of the Nigerian stock market and believes that there is a positive relationship between macroeconomics and stock markets. His study also lacked a structure to quantify resilience. Chen and Siems [29] compare the resilience of the US stock market with the other countries and conclude that the most resilient level belongs to the US. They develop three indices to measure the resiliency of stock markets: the abnormal market indices, the cumulative abnormal market index, and the days to recover the market performance after a shock. They were the first to associate resilience with a simultaneous view at the amount of performance decline and recovery time, and attributed a pseudo-quantitative amount to resilience. Nevertheless, despite the fact that the subject of their study was the shock of terrorist attacks, the market index was evaluated directly.

Alabed and Al-Khouri [30] use different liquidity ratios to analyze markets' resilience. Their proposed ratios are 1) liquidity ratio 1: rate of the total volume of deals to return, 2) Liquidity ratio 2: rate of the total volume of deals to return multiply the difference in the number of shares in two years, and 3) Liquidity ratio 3: rate of return to the total number of deals. They propose different logical relations between the higher liquidity ratio and the resilience. For example, they find that a higher liquidity ratio of 3 will leads to lower resilience. Lack of quantitative calculation of resilience and its inability to compare different situations was the most important weakness of their study.

Wanzala et al. [31] consider a function of variance rate as resilience. Their proposed function is the ratio of the number of periods multiplied by the seasonal variance of the return divided by the annual variance of the return. Using annual data will have the weakness of not examining more details and monthly changes. Of course, not paying attention to the concept of return period was another challenging point of their work.

Rezaei Soufi et al. [32] present a study about the resilience of companies in the stock market. They examine the share price decline level in the various shocks inflicted on companies and investigate their resilience by three approaches: the share-price method, *VaR* of share price, and *CoVaR* based on the cause of the shock. Modifying the total market index from the point of view of resiliency due to the systemic risk, and most importantly, modifying the resiliency according to the performance trend in the period of decline and recovery is the most important point that was not in the scope of their study.

Since the concept of resilience in stock markets is related to stock index which is very volatile; therefore, it is necessary to consider the direct effect of shock damaged the system and suffix the performance index. Also, in many cases, the value of the performance index does not return to the previous value for a long time, so it is necessary to develop an approach for the concept of recovery in the financial performance index for this case.

As mentioned, another issue in this concept is the pattern of reduced performance during and after the shock. In the concept of organizational resilience, the goal is to return to pre-disaster levels, and there was no sensitivity to the two situations of: 1) slow decline and fast return of performance index, and 2) rapid decline and slow return of performance index, while in the financial markets, the ability to withstand the shock and maintain performance in the phase of collapse and recovery after the disaster is different in nature from a time point of view.

According to studies such as [29], [31], and [10], resilience in the stock market faces several challenges that have received less attention in the literature. The most important challenges are high volatility issues, the direct effect of shock, which is considered in *CoVaR*, recovery time, and the pattern of decrease and increase in financial performance. Main features of the issue and the relevant papers are reviewed in Table 1.

Please insert Table 1 about here.

As a supplementary point, the resilience index should be able to express the state of continuity of a system in the face of shock. Allocation of qualitative variables to resilience alone cannot be a good situation for comparing systems, while in Basel III [27] and Ovat [28], only qualitative resilience values are presented. On the other hand, resilience should be able to simultaneously take into account the amount of resistance against collapse and shortening the time remaining in the crisis period, while only one aspect is considered in the articles of Alabed and Al-Khouri [30] and

Wanzala et al. [31]. Also, among the few papers that have considered both aspects, improvement of the index by considering the effect of systemic risk has been considered only in Baig et al. [10]. Also, due to the fact that the pattern of decline and return of the index is very important in financial systems, none of the articles have paid attention to this issue.

In this study, we aim to examine the resilience of stock markets of seven Middle East countries to cope with oil prices shock as an external factor. Notably, the scope of this paper is only the analysis of the resilience behavior of capital markets according to oil price changes. In this manner, first, we use the link between stock market index and oil price, applying the *CoVaR* concept to calculate the systemic risk.

Therefore, the shock of oil price reduction in 2020 and the historical shocks of 2008, 2014 and 2023 are examined.

Accordingly, the main contributions of this study are as follows.

Developing a modified quantitative measure to calculate the resilience of the stock market in order to evaluate the market behavior in oil price shocks by considering: performance reduction and relevant period of the shock;

Considering the patterns of declining and recovering in terms of speed of performance change for the calculation of resilience;

3. The Proposed Methodology

In this section, we first analyze the effect of the oil price shock on the stock market by calculating systemic risk. Next, a measure has been developed to calculate the resilience of the stock markets. Figure 2 depicts the main steps of the proposed study.

Please insert Figure 2 about here.

3.1. Systemic risk calculation of stock markets due to the oil price shocks

This section uses the systemic risk and the *CoVaR* measure to investigate the fluctuations of oil prices in the stock markets.

3.1.1. CoVaR of Oil price and stock market index

To investigate the *CoVaR* of oil price and stock market index, let us assume that x_t is the stock market index at time t, x_t^o is the oil price at time t, and superscript f shows the studied countries. Accordingly, the *CoVaR* at *(1-β)%* confidence level can be calculated based on the β^{th} percentile of the conditional distribution of x_t^f by equation (1).

$$\Pr(x_t^f \leq CoVaR_{\beta,t}^{f|o} \,\big|\, x_t^o \leq VaR_{\alpha,t}^o) = \beta \tag{1}$$

As a measure of stock market performance, this paper uses the stock market index of each country. Accordingly, in equation (1), the expression $VaR_{\alpha,t}^o$ shows the *VaR* of oil price, explained as the maximum loss experienced in the oil market at *(1-α)*% confidence level at time t. Since α and β show the confidence levels of the two different markets, they are not necessarily the same. Assuming a portfolio comprising only one crude oil item and considering $\Pr(x_t^o \leq VaR_{\alpha,t}^o) = \alpha$ the

CoVaR will be calculated using the β^{th} percentile of an unconditional bivariate distribution of the oil market and stock market variables (equation 2).

$$\frac{\Pr(x_t^f \le CoVaR_{\beta,t}^{f|o} \left| x_t^o \le VaR_{\alpha,t}^o \right.)}{\Pr(x_t^o \le VaR_{\alpha,t}^o)} = \beta \tag{2}$$

Summarizing equation (2), we obtain $\Pr(x_t^f \le CoVaR_{\beta,t}^{f|o}, x_t^o \le VaR_{\alpha,t}^o) = \alpha\beta$.

According to Mainik & Shaanning [23], the final value of systemic risk will be calculated as equation (3).

$$\text{Systemic risk} = \frac{CoVaR^{f|o}{}_{\alpha,\beta}(F,O)}{VaR_\alpha(O)} - 1 \tag{3}$$

To calculate the *CoVaR*, the joint distribution of *f(x,y)=z* using the Copula model, should be applied.

3.1.2. The CoVaR concept accompanied by Copula

Previous studies show that financial data have heavy-tailed distribution, and direct approximation of them using popular statistical distributions will cause significant calculation errors [33]. The Copula method will be used for investigating the dependencies and correlations to model these data adequately. Here, the Copula concept has been used to evaluate the joint distribution of the oil market and stock market variables. Hence, equation (2) can be written as equation 4.

$$F_{f,o}(CoVaR_{\beta,t}^{f|o}, x_t^o \le VaR_{\alpha,t}^o) = \alpha\beta \tag{4}$$

where $F_{f,o}$ is the bivariate joint density function of the oil and stock markets. Moreover, the joint distribution function using the Copula concept can be described as equation (5).

$$F_{f,o}(x^f, x^o) = C(u_f, u_o) \tag{5}$$

Where $C(.,.)$ is the Copula function, $u_f=F_f(x_t^f)$ and $u_o=F_o(x_t^o)$, F_f is the variable of the marginal distribution of x_t^f, and F_o is the variable marginal distribution of x_t^o. Accordingly, equation (4) can be written as equation (6).

$$C(F_f(CoVaR_{\beta,t}^{f|o}), F_o \le VaR_{\alpha,t}^o) = \alpha\beta \tag{6}$$

The *CoVaR* can be calculated by having the known values of α and β. The calculation of joint distribution parameters will be performed using a two-stage approach proposed by Yang et al [34]. First value of $F_f(CoVaR^{f|o}{}_{\beta,t})$ is determined using equation (6). Next, considering the equation $C(u_f,u_o)=\alpha.\beta$ the u_f will be calculated considering the known values of β, α and u_o. In order to calculate $u_f= F_f(CoVaR^{f|o}{}_{\beta,t})$, the desired inverse equation will be written. Using Copula, it gives the model the capability to consider other different assumptions for the dependency between the distributions of the variables. In Copula models, to increase the accuracy of the model, it is recommended to use marginal distributions to analyze index and variance of index. Accordingly, the *ARMA(p,q)* for index and *TGARCH* model for variance is applied. Copula has this tendency to parametric bivariate functions that consider different structures for the dependence of variables. These dependency functions can also provide various features of the distribution tail. Due to the different structure of the tail, six different cases of dependencies have been considered for the Copula function as follows: Gaussian and Plackett distributions when the distribution tail is independent; t-student distribution when the distribution tail has symmetric dependency; Gumbel, rotated Gumbel and BB7 distributions when the distribution tail has an asymmetric dependency. We use the maximum likelihood estimator to calculate each Copula model's parameters.

3.2. Calculating the resilience of stock market

According to the resilience definition, the proposed model should consider the effect of shock on performance reduction and recovery time. Hallegatte [35] defines economic resilience as the value of lost assets of an economy during a disaster. In his viewpoint, resilience is related to decreased functionality in case of disaster and time to recover the economy's functionality back to the normal level. Chen and Siems [29] claim that market cumulative abnormal return and the days to recovery are two main aspects of resilience which can be used to develop the resilience function. We use the Hellegatte [35] idea for economic resilience and apply the Chen and Siems [29] definition to develop a method for calculating the resilience of the stock markets.

3.2.1. Identifying recovering time and decreasing index

Figure 3 shows our proposed methodology for calculating stock market resilience. According to this figure, abnormal market index occurred after occurring a shock. Hence, the area under the stock market index (*SMI*) curve shows the total loss of resilience for the stock market (*LORSM*) during the recovery time. Of course, other measures can also be used to analyze the situation. For example, in Iazzolino et al [36], a regression index was developed based on several metrics for the performance of companies in the market, however, in this paper, the presented market index is used. This area is related to two variables of recovery time and stock market index (*SMI*) reduction. Notably, recovery time is the time between occurrences of a shock and recovering the SMI to the baseline. The decreased level is the level of reduction after the oil price shock. So, the lower area of stock market index reduction and shorter recovery time leads to a higher level of resilience.

Please insert Figure 3 about here.

3-2-2. Measuring the degree of resilience of stock market (DORSM)

According to figure 3, the degree of resilience of the stock market (*DORSM*) is equal to 1- loss of resilience for the stock market (*LORSM*) and calculated by equation (7).

$$DORSM = 1 - LORSM = 1 - \frac{\int_{t_1}^{t_2} F(SMI)dt}{\min F(SMI) \times (t_2 - t_1)} \tag{7}$$

Where *Min(SMI)* is the worst level of *SMI*, t_1 and t_2 are the beginning and end times of the oil price shock (or disaster) period, respectively. *F(SMI)* is the behavior of *SMI* in the disaster period.
As mentioned in the previous sections, the most important challenge in discussing resilience is to determine the system's resilience for different specific shocks. Therefore, with a modification in the function shown in equation (7) and the diagram presented in Figure 4, resilience has been

modified by converting the SMI to the SMI status due to systemic oil price risk. Figure 4 shows the amount of resilience caused by this shock by considering only the oil price risk. According to this figure, the minimum performance value is higher than the overall minimum so that it considers only the oil price risk. Therefore, all the values observed in the *SMI* will be corrected, and the recovery time (t_2 value) will also be shorten. Thus, the total resilience based on the oil price shock will be as equation (8).

Please insert Figure 4 about here.

$$DORSM \mid oil\ price\ systemic\ risk = 1 - LORSM = 1 - \frac{\int_{t_1}^{t_2} f\,(SMI \mid oil\ price\ systemic\ risk)\,dt}{\min(F(SMI \mid oil\ price\ systemic\ risk) \times (t_{2|oil\ price\ systemic\ risk} - t_1)} \tag{8}$$

3-2-3. Developing the approximate method to calculate DORSM

A set of geometric shapes can be placed in the *DORSM* area to simplify the *DORSM* equation. Figure 5 presents different modes of *DORSM* area, including a triangle and a combination of a triangle and a trapezius. Here, instead of integral, we can calculate the area of geometric shapes.

Please insert Figure 5 about here.

3.3. Adjusting the resilience function

There are several challenges in the basic approach proposed in the previous section to calculate resilience. The basic model in equation (8) cannot distinguish between different diagrams in figure 6, in which the pattern of changes in them is different.

Furthermore, the start and endpoints of the disaster period cannot be determined easily. Here, we identify different models for resilience function, which consider the pattern of the *SMI*. According to figure 6, there are different *SMI* patterns from the onset of a disaster until its recovery. This recovery time involves two phases of decreasing and increasing the *SMI*. In the different models of figure 6, the slope of the decreasing and increasing phases can have different patterns. This section attempts to modify equation (8) to develop a function that can distinguish between the four different models of resilience. In model *a* (sharp decrease-soft increase model), the fall to the local minimum point is intense, but the return to the uptrend is slow. The system responds rapidly to shock and is adversely affected. However, it is not able to return quickly and is eroding. The decreasing phase is slow in model *b* (soft decrease-sharp increase model), while a quick return happens. In model *c* (soft decrease-soft decrease model), both decreasing and increasing phases occur with similar slopes (slow or rapid). Finally, in model *d* (sharp decrease-sharp increase model), it can be seen as a situation where an inverse pattern occurs during the decreasing or increasing phase. In this model, it is important to consider whether the return value has been able to pass a threshold value limit or not.

Please insert Figure 6 about here.

In the four considered models, the lower slope for the decline in the *SMI* shows the higher resistance in market return, and the higher slope in the returning phase shows a higher tendency to recover. Therefore, a coefficient factor can be entered into the model using these slopes. The proposed function of resilience would be adjusted as shown in equation (9).
It is notable that t^-, t^+, and t^o are the start of decreasing phase, the start of the increasing phase, and the time of minimum *SMI*, respectively. Moreover, a turning point identification algorithm was used to identify the t^- and t^+. The difference in these points and the difference in the pattern of sharp acceleration and slow return, or vice versa, has made equation (8) into two distinct parts in the two periods of decline and return. Also, the coefficients of α, β, and ψ are the adjusted and normalized coefficients associated with the slope of decline and return.

$$DORSM = 1 - LORSM = 1 - \left[\begin{array}{l} \psi\left(\dfrac{\int_{t^-}^{t^o} f\,(SMI \mid oil\,price\,systemic\,risk)dt}{\min F(SMI \mid oil\,price\,systemic\,risk)*(t^o - t^-)}\right) + \\ (1-\psi)\left(\dfrac{\int_{t^o}^{t^+} f\,(SMI \mid oil\,price\,systemic\,risk)dt}{\min F(SMI \mid oil\,price\,systemic\,risk)*(t^+ - t^o)}\right) \end{array} \right] \tag{9}$$

Where:

$$\alpha = \frac{\left| \dfrac{\min F(SMI) - F(SMI^{t^-})}{F(SMI^{t^1}) - F(SMI^{t^o})} \right|}{\dfrac{t^o - t^-}{t^2 - t^1}} \tag{10}$$

$$\beta = \frac{\dfrac{t^+ - t^o}{t^2 - t^1}}{\dfrac{F(SMI^{t^+}) - F(SMI^{t^o})}{F(SMI^{t^2}) - F(SMI^{t^o})}} \tag{11}$$

$$\psi = \frac{\alpha}{\alpha + \beta} \tag{12}$$

The next step is to identify the starting and resuming points of the financial performance. To this point, method of Rezaei Soufi et al. [32] has been utilized. They used the turning points to identify the disaster period in macroeconomic resilience calculation. With this idea, the points are identified where the trend change in the state of the *SMI* occurred in the periods with the oil shock. For this purpose, the return of the *SMI* is calculated based on the previous time period, and by comparing the recent return data, the trend change (from several consecutive positive or constant returns to a number of negative returns or vice versa) is identified and the equivalent *SMI* is identified at the turning points which is used in the calculations of equation (9). The algorithm for identifying the turning points is presented in Section A of Supplementary file.

4. Implementation of the proposed methodology

This section provides step-by-step explanations for resilience evaluation for seven stock markets due to fluctuations in oil prices.

4.1. Data

Eight types of data were collected to analyze the stock market resilience resulting from the oil prices' changes in the selected markets. The required data were collected from the investing.com website and the stock exchange websites of the seven countries.

Since the recovery calculation model needs to calculate the start and end times of disaster periods, there is a major challenge in choosing this period. The period should incorporate as much data as possible and should not be so fluctuating that it is difficult to extract a pattern. It should be noted that consecutive negative or positive return of indices are needed to start or end the disaster period in the developed quantitative algorithm, while high data fluctuations reduce the likelihood of this. The first challenge confirms the use of data with a short time period, such as daily, and the latter leads to the use of data with longer time periods, such as monthly data. This paper attempts to use maximum data with the least fluctuations by eliminating the noise in daily data. Furthermore, sequences with negative or positive index’s returns are required to extract a pattern to determine the beginning and ending of a disaster. Examination of the data shows that it is impossible to extract strong patterns due to high data fluctuations. Therefore, in order to simultaneously use a high data range and reduce the risk of data fluctuations, the noise in the data needs to be eliminated so that a smoothing pattern of data can be extracted. For this purpose, first, by segmenting the data in different disaster periods and then by eliminating the data noise, an appropriate approach is applied to determine the starting and ending of the disaster. In this manner, first using an important point method by identifying the local minimum and maximum points, the markets are segmented into different groups [37].

Then, data from each period are de-noised using the *EGARCH* noise recognition algorithm introduced by Feng et al. [37] (see Section B of Supplementary file). Examination of the data trend after noise removal shows that the oscillation of daily data has decreased to some extent, and the possibility of pattern extraction from these data has increased. In order to check the changes in the market situation, instead of evaluating the index itself, the return of each sector has been checked here. Table 2 presents the descriptive statistics of the market returns for the seven countries as well as the oil price changes. Other statistical analyses are presented in table C-1 in Section C of Supplementary file .

Table 2 also provides the results of the data normality, autocorrelation, and heteroscedasticity tests through the Jarque-Bera, Ljung-Box, and heteroscedasticity tests. It can be seen from Table 2 that the normality assumption of the return cannot be proved for the eight series of our data; hence, there is autocorrelation (especially sectional) between the data. Furthermore, the heteroscedasticity test results indicate this effect's significance in all data.

Please insert Table 2 about here.

4.1. Systemic risk calculation results

To analyze the relationship between the decrease in the 2020 oil price shock and the decrease in the stock market index in the seven countries, we evaluate the correlation between the SMI of each country and the oil price changes in two time spans relevant to before and after the decrease in the oil prices. Dobromirov et al [38] developed an applicable method for correlation calculation. Results show that such a correlation is significant and has been even more significant during the decrease in oil prices. Table 3 shows the detail of the findings. The results show that after the oil price shock, the correlation between the stock market index and the oil prices has escalated in all countries.

Please insert Table 3 about here.

Using the different Copula models described in section 3.1.2, the correlation test between the seven understudy countries' stock markets and the oil price changes is analyzed. The best Copula model will be the model with the best Akaike value. Our results show that only for Bahrain, the static Copula models are acceptable, while for the other countries, it would be better to use a dynamic model for approximation with Copula. Furthermore, results show that for Iran, Qatar, and Kuwait, the Plackett model, for Oman and Saudi Arabia, the Gumbel model, for UAE the t-student model, and for Bahrain, the Gaussian Copula models are the best models, respectively. The data indicate a significant negative correlation for Qatar, while this correlation for other countries has positive values. Nevertheless, as was mentioned, the absolute value of correlation has increased after the advent of the 2020 oil price shock.
Considering the best Copula models selected in the previous section and the process mentioned in section 3.1, the *CoVaR* is calculated for both pre and post-oil price shock. For the calculation of the *CoVaR*, a confidence level of 95% is considered, which requires β to be set as %5. Similarly, for the conditional variable, the confidence level is also determined as %95 (i.e., α = %5 and λ = %5). Now, by employing the selected Copula models, the best values for systemic risk can be calculated. We test the significance of the relationship between oil price shock and stock market index. Considering the outputs mentioned in previous sections, we observe that the seven countries' stock market has undergone changes due to the oil price shock effects. Suffice it to calculate the *CoVaR* using the three steps method mentioned in section 3.1. Here again, the calculations are performed in two states of pre and post-oil price shock. The results indicate an improvement in systemic risk calculation using the *CoVaR* instead of the *VaR* method. Table 4 shows the related results for the two states of pre and post-oil price shock. The rows of Table 4 represent the *VaR* and *CoVaR* values for the seven understudied stock markets considering the oil price fluctuations.

The values show that in the pre-oil price shock era, the presence of countries in oil markets has been a risk of reducing the stock markets' index for all seven countries.

Please insert Table 4 about here.

In the post-oil price shock era, it can be observed that in the countries which are experiencing the highest systemic risk from the oil price shock (UAE, Bahrain, and Kuwait), the systemic risk has been critically escalated for them after the advent of the shock. The mean of the *CoVaR* value has been decreased to a lower level. This seems totally true because the values of the *CoVaR* as measures of risk are negative, and the more negative state of the *CoVaR* for these countries indicates the more appropriate performance of this measure relative to the *VaR* measure.

4.2. Stock market resilience

In this study, our proposed model in sections 3-2 is applied to calculate the resilience of the seven stock markets. According to Chen and Siems [33], the cumulative abnormal return of the market and the days to recover are two main aspects of resilience used to develop the resilience function. According to figure 5, the area under the *SMI* shows the total degree of resilience of the stock market during the recovery time. The stock market index, *SMI*, and *DORSM* of seven understudied countries are presented in Section D of Supplementary file. It should be mentioned that due to the scale of the data and the largeness of the index, the logarithm of *SMI* of the studied countries was used so that the trends and changes can be easily examined and compared. As shown in figure 5, different modes of *DORSM* area include a triangle and the combination of a triangle and a trapezium, which can be placed in the *DORSM* area .

Also, the disaster period for each country is specified according to section 3.4, and the exact and approximate amount of resilience is estimated using equation (9) and the approximate models proposed in section 3.3. Table 5 shows the 2020 oil price shock results for different countries.

Notably, according to the maximum slope value (0.63), the slopes less or more than 0.4 are considered soft and sharp, respectively. It seems that the results for *DORSM* for exact calculation using equation (9) and the approximate method based on figure 4 have no significant difference in the 95% confidence level.

Please insert Table 5 about here.

5. Discussion

In this section, we discuss the stock markets' resilience during historical oil price shocks. Due to the available data, we consider the 2008, 2014, and recent 2023 oil price shocks and test whether the stock markets with higher historical resilience are more resilient than others in the 2023 oil price shock. Furthermore, we want to find the reasons for the lower or higher level of resilience which leads to risk reduction.

5.1. Stock market resilience and historical oil price shocks

We use data from the seven understudied stock markets during the 2005 to 2023 and calculate the systemic risk and approximate amount of their resilience. In the 2008 disaster, the oil price decreased by 70% in 7 months, in the 2014 disaster, the oil price decreased by 68% in 18 months, and in the 2023 oil price reduction, it is decreased by 42% in 10 months. Table 6 shows the relevant results.

According to table 6, we can see that the countries with higher *DORSM* in 2008, 2014, and 2023 oil price shocks (i.e., Qatar, Iran, and Oman) have a better performance during the 2020 oil price shock, while the countries with lower *DORSM* in 2008, 2014, and 2023 oil price shocks have seen more damages from 2020 oil price shock with 95% confidence level. Furthermore, countries with lower systemic risk are historically having better performance in the 2020 oil price shock.

Please insert Table 6 about here.

5.2. Reasons for resilient stock markets

In this step, we analyze the reasons for higher resilience. In this manner, we analyze the seven understudied countries and evaluate the reasons for higher resilience using qualitative and quantitative analyses. For the qualitative analysis, we use several criteria as the reasons for being less resilient based on the National bank of Danmark's report [39] in stock markets as follows: 1) variety of different industries in stock markets, 2) using new financial instruments in the stock market, 3) transparency of information in the stock market, and 4) credit obligation mechanism in the stock market.

Analyzing the situation of different stock markets, we find number of industry sectors in Saudi Arabia, Qatar, UAE, Oman, Kuwait, Bahrain, and Iran are 21, 18, 13, 15, 16, 8 and 37, respectively. Furthermore, using derivative as one of new financial instruments in these markets are approximately zero for Saudi Arabia, Qatar, Oman, and Bahrain, lower than 2% of market size in Iran, and UAE, and about 5% in Kuwait. The credit obligation for all countries are almost the same [40]. Finally, transparency in Iran and Bahrain is weak, however, for the other countries is better than two mentioned countries [41]. Accordingly, we contend the following results.

Countries with lower rate of diversification (i.e., Bahrain, and UAE) have a lower level of the *DORSM*.

The penetration coefficient of new financial instruments in the seven understudied countries is low. However, derivatives are more common in Iran, UAE, and Qatar than in other countries. We can see that these countries are almost more resilient than the others.

Transparency of information and credit obligation mechanism of the stock markets is almost the same, which does not provide any meaningful differences.

For the quantitative analysis, we use the liquidity ratio proposed by Alabed and Al-Khouri [30], the volatility ratio proposed by Wanzala et al. [31], and the skewness/ kurtosis of the stock market index proposed by Bali et al. [42] to test the ability of the model. We use historical data to calculate skewness, kurtosis, liquidity ratio 3, and variance ratio of the stock market index during the historical oil price shocks. In this manner, we use the data from one year before and one year after the occurrence of the oil price shock to test the relationship between them and resilience. The results are shown in Table 7.

Please insert Table 7 about here.

According to table 7, on average Qatar, Oman, and Iran, which have the highest *DORSM*, have a lower kurtosis value in oil price shocks, while UAE, Bahrian, and Saudi Arabia, with a lower *DORSM*, has the biggest value of kurtosis. Moreover, the stock markets with a higher level of *DORSM* (i.e., Qatar, Oman, and Iran) have higher values of skewness in comparison to the stock markets with a lower level of *DORSM*. This is rational because Saudi Arabia and UAE have huge skewness and kurtosis values. It means that before the oil price shock, the stock market of these countries has gone through a growth period with a relatively uniform positive slope over a long period of time, and suddenly, it has experienced a sharp upsurge in the market index (negative skewness). Moreover, the stock market index of Saudi Arabia has a large pointedness of a peak in the stock market curve (large kurtosis). Naturally, these two will lead to a lower level of *DORSM*. This logical analysis can also be extended to other countries. To have a more detailed analysis, we test the relation between skewness and kurtosis of the stock market index with the *DORSM* of the stock markets. According to table 7, the markets with lower kurtosis are more resilient. It is rational because these countries were more stable during historical disasters. Also, regarding the liquidity rate index and variance rate, in Alabed and Al-Khouri [30], and Wanzala et al. [31] studies, it has been shown that a higher value of the liquidity rate and variance rate reduce the resilience. Calculating these two indicators shows that the results of resilience analysis from the calculation of liquidity rate and variance rate are primarily consistent with the amount of the *DORSM*. However, despite the correct separation between different countries in each period, the results in two consecutive periods are not comparable. This is mostly due to differences in disasters' severity, efficiency, and volatility values. The results of this section can be considered as approaches to risk reduction by increasing the resilience.

In order to show the power of the method developed in this paper in modifying the resilience calculation, we compare the results of resilience of countries in 2020 in three following situations, 1) Resilience calculation using main formula (based on Figure 1-a), 2) Resilience calculation based on the systemic risk factor (Figure 1-b), and 3) Resilience with the correction factor of the fall rate and return period (Figure 6). Then comparing the three resilience values with the economic growth rate of countries in 2019, 2020 and 2021 (see table 8). The results show that the use of our final model of equation (9) is closer to the real situation of countries based on growth rate changes. For example, for Kuwait which has the lowest growth rate, resilience values with main formula and the *CoVaR* coefficient is higher than Bahrain while with decreasing/recovery trend coefficient its resilience value is the lowest between seven countries. This analysis could be extended for the other countries.

Please insert Table 8 about here.

6. Conclusion and policy implications

The decrease in oil prices has affected the stock markets of oil suppliers' countries. In this study, to accurately investigate stock market resilience, the *CoVaR* measure was used to measure the effect of oil price shock on the stock markets of seven Middle East countries. Furthermore, a formula is developed to calculate the resilience of stock markets. In addition, the equation is adjusted based on the effect of systemic risk and different patterns in disaster time period. An approximate approach was also developed to facilitate the process of calculating resilience.

Considering our results from the calculation of the *CoVaR*, the following results can be concluded:

The positive correlation between crude oil price and countries' stock markets can be observed.

Comparing the two *CoVaR* and *VaR* measures, we find the superiority of the *CoVaR* measure compared to the *VaR* measure based on the results of the Kolmogorov-Smirnov statistics.

Our findings of resilience can be summarized as follows:

Our proposed *DORSM* mehod reflects both the stock market performance decreasing and the corresponding disastrous time periods.

It seems that the results for the *DORSM* for the exact calculation using equation (7) and the approximate method are not significantly different at a 95% confidence level. Indeed, both our developed methods worked well.

Modifying the *DORSM* with decreasing and recovering trend coefficient increase the capability of our resilience measure.

The countries with higher resiliency in the 2008, 2014, and 2023 oil price shocks have a better performance during the 2020 oil price shock. So, the analysis of the structure of stock markets can reveal the reasons for the higher level of resilience.

At the end of this paper, reviewing the experiences of different countries, a set of policies to enhance the resilience of the stock market is presented.

Various industries in stock markets can increase the resilience of the stock market. Our reviews show that countries with more diversified industry groups have better performance during oil price shocks.

New financial instruments in the stock market increase the resilience of the stock market. The results reveal that countries that focused on derivatives were more resilient.

Planning to record experiences in different crises can be used in future crises and increase the resilience. Note that the type of market index fall patterns should be considered in resilience analysis.

Future research can focus on other oil supplier/demander countries as well as to consider oil construction and prediction. As another idea, given the starting point of the disaster period between different countries, as a topic, future studies can address the differences in the starting point of the stock market's disaster as well as the contagion among the countries using methods such as Copula and Vine-Copula. Future studies could also use more sophisticated turning point approaches to identify disaster periods.

The supplementary data is available at: file:///C:/Users/pc/Downloads/Supplementary%20File-SCI-2308-8108.pdf

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Table 1. Main features of the related studies in the literature

Reference	Subject of study			Risk measures		Resilience	Understudied countries	Oil price shock duration
	Macroeconomic	Financial institutions	Stock market	VaR	CoVaR			
Chen and Siems [33]			✓			✓	US, China	-
Alabed and Al-Khouri [30]		✓				✓		-
Fayyad and Daly [7]			✓				Kuwait, Oman, UAE, Bahrain, Qatar, UK, and the USA	2006-2010
Adrian & Brunnermeier [13]		✓			✓		USA and European countries	-
Mainik & Shaanning [23]	✓				✓			-
Ovat [28]			✓	✓			Nigerian market	-
Wanzala et al. [31]			✓			✓		-
Chatziantoniou et al. [11]	✓		✓		✓			1997-2020
Baig et al. [10]			✓			✓	Pakistan	2020
Rezaei Soufi et al. [3]		✓		✓	✓	✓	Iran	-
Current study			✓	✓	✓	✓	7 Middle East countries	2005-2023

* VaR-Value at risk; CoVaR (conditional value at risk)

Table 2. Descriptive statistics of the data and statistical test results

	Oil price	**Saudi Arabia**	**Qatar**	**UAE**	**Oman**	**Kuwait**	**Bahrain**	**Iran**
Mean return	-0.00011	-0.00005	-0.00009	-0.00005	-0.00008	0.00005	0.00008	0.00143
Standard deviation	0.02507	0.01456	0.01315	0.01625	0.00906	0.00902	0.00473	0.00977
Minimum	-18.61%	-9.39%	-9.42%	-12.20%	-8.04%	-12.82%	-3.42%	-7.65%
Maximum	17.14%	10.33%	10.21%	12.16%	8.69%	14.68%	6.01%	6.34%
J-B	16325.05	5119.46	2319.68	4316.95	7761.3	1265.5	743.9	1011.28
Q(20)	16.592 [0.002]	10.669 [0.000]	14.652 [0.012]	26.55 [0.010]	55.79 [0.005]	40.29 [0.009]	16.54 [0.063]	63.29 [0.045]
ARCH	13.72 [0.049]	12.57 [0.020]	8.33 [0.009]	17.32 [0.025]	19.06 [0.041]	9.06 [0.018]	10.12 [0.004]	18.29 [0.013]

Note: J-B is Jarque-Bera statistic test of normality, Q(m) is the Ljung-Box statistic for serial correlation in squared returns computed with *m* lags, and ARCH denotes Engle's LM test for heteroscedasticity computed using 20 lags.

Table 3. Correlation of countries' stock market and oil price changes before and after 2020 oil price shock

		Saudi Arabia	Qatar	UAE	Oman	Kuwait	Bahrain	Iran
Correlation with oil price shock	Total	0.3311	0.6318	0.6065	0.4029	0.6293	0.5256	0.5329
	Before oil price shock	0.2542	0.5604	0.5367	0.3562	0.5503	0.4212	0.54433
	After oil price shock	0.4123	0.6991	0.6852	0.4825	0.7233	0.5716	0.6001

Table 4. The results of the *CoVaR* calculation for the 2020 oil price shock

		Pre-oil price shock		Post-oil price shock	
		Mean	**Standard deviation**	**Mean**	**Standard deviation**
Saudi Arabia	*VaR(f)*	-0.0490	0.0300	-0.0835	0.0617
	CoVaR(f|o)	-0.0390	0.0327	-0.0980	0.0463
Qatar	*VaR(f)*	-0.0174	0.0123	-0.0221	0.0282
	CoVaR(f|o)	-0.0156	0.0338	-0.0333	0.0449
United Arab Emirates	*VaR(f)*	-0.0705	0.0252	-0.1253	0.0670
	CoVaR(f|o)	-0.0565	0.0226	-0.1679	0.0574
Oman	*VaR(f)*	-0.0365	0.0449	-0.0739	0.0393
	CoVaR(f|o)	-0.0309	0.0299	-0.0880	0.0571
Kuwait	*VaR(f)*	-0.0576	0.0378	-0.1070	0.0513
	CoVaR(f|o)	-0.0378	0.0315	-0.1295	0.0800
Bahrain	*VaR(f)*	-0.0647	0.0251	-0.0956	0.0405
	CoVaR(f|o)	-0.0463	0.0309	-0.1235	0.0463
Iran	*VaR(f)*	-0.0328	0.0487	-0.0778	0.0365
	CoVaR(f|o)	-0.0272	0.0440	-0.1021	0.0515

Note: The table shows the mean and standard deviation of the *VaR*-Value at risk; *CoVaR*- conditional value at risk at the 95% confidence level for stock market index and oil price in the pre- and post-oil price shock periods using the best copula fit. *CoVaR*(*f*|*o*) denotes the *CoVaR* of the stock market index conditional on the fact that the oil price is in shock.

Table 5. *DORSM* results for seven understudied countries during the 2020 oil price shock

Country	**Start of disaster**	**End of disaster**	**Model**	**Exact value of modified *DORSM* using equation (9)**	**Approximate amount of modified *DORSM* based on Figure 4**
Saudi Arabia	Jan-20	Apr-20	Sharp-Sharp	0.648	0.613
Qatar	Jan-20	Apr-20	Sharp-Sharp	0.686	0.665
UAE	Dec-19	Apr-20	Sharp-Soft	0.590	0.594
Oman	Jan-20	May-20	Sharp-Soft	0.707	0.705
Kuwait	Jan-20	Apr-20	Sharp-Soft	0.562	0.575
Bahrain	Dec-19	May-20	Sharp-Sharp	0.577	0.561
Iran	Jan-20	Apr-20	Soft-Sharp	0.765	0.741

Table 6. *DORSM* results for seven understudied countries during 2008, 2014, and 2023 oil price shocks

Country	**2008 oil price shock**		**2014 oil price shock**		**2023 oil price shock**	
	Mean of *CoVaR(f|o)*	**Approximate amount of modified *DORSM* (Figure 4)**	**Mean of *CoVaR(f|o)***	**Approximate amount of modified *DORSM* (Figure 4)**	**Mean of *CoVaR(f|o)***	**Approximate amount of modified *DORSM* (Figure 4)**
Saudi Arabia	-0.132	0.465	-0.112	0.278	-0.051	0.664
Qatar	-0.032	0.846	-0.014	0.889	-0.006	0.687
UAE	-0.089	0.613	-0.069	0.634	-0.032	0.644
Oman	-0.074	0.848	-0.059	0.779	-0.027	0.752
Kuwait	-0.116	0.780	-0.084	0.87	-0.039	0.683
Bahrain	-0.101	0.584	-0.065	0.754	-0.030	0.674
Iran	-0.098	0.887	-0.085	0.796	-0.039	0.691

Note: the mean of *CoVaR(f|o)* denotes the conditional value at risk (*CoVaR)* of the stock market index conditional on the shock in oil price, and the approximate amount of DORSM is calculated.

Table 7. Values of skewness and kurtosis of the stock market index during historical oil price shocks

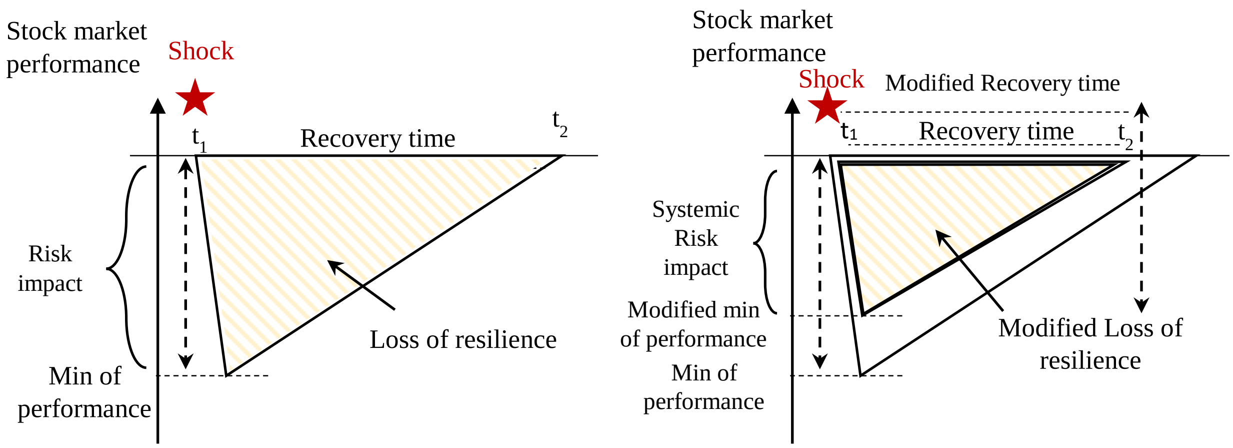
Country	**2008 oil price shock**					**2014 oil price shock**					**2020 oil price shock**					**2023 oil price shock**				
	Skewness of index	**Kurtosis of index**	**Liquidity Ratio**	**Variance Ratio**	**DORSM**	**Skewness of index**	**Kurtosis of index**	**Liquidity Ratio**	**Variance Ratio**	**DORSM**	**Skewness of index**	**Kurtosis of index**	**Liquidity Ratio**	**Variance Ratio**	**DORSM**	**Skewness of index**	**Kurtosis of index**	**Liquidity Ratio**	**Variance Ratio**	**DORSM**
Saudi Arabia	-8.03	53.16	$1.903*10^{-7}$	4.956	0.47	-6.18	33.43	$9.142*10^{-8}$	5.2362	0.29	-3.14	31.09	$1.267*10^{-8}$	3.6512	**0.613**	-5.22	38.38	$9.423*10^{-9}$	4.2116	0.664
Qatar	-5.57	34.05	$9.219*10^{-8}$	2.647	0.85	-3.91	27.62	$1.654*10^{-8}$	3.2841	0.92	-3.26	25.45	$1.023*10^{-8}$	3.4214	**0.665**	-3.14	26.52	$7.255*10^{-9}$	3.6914	0.683
UAE	-2.35	62.27	$1.852*10^{-7}$	4.129	0.61	-1.88	33.14	$2.353*10^{-8}$	4.2167	0.65	-7.63	39.86	$5.296*10^{-8}$	4.1309	**0.554**	-6.92	41.14	$3.462*10^{-8}$	4.8523	0.644
Oman	-1.29	53.52	$1.032*10^{-7}$	2.966	0.85	-0.52	25.25	$1.993*10^{-8}$	3.9023	0.78	-1.99	19.99	$9.625*10^{-7}$	3.6214	**0.705**	-0.29	18.42	$7.028*10^{-9}$	3.6215	0.752
Kuwait	0.06	36.36	$1.399*10^{-7}$	3.243	0.78	0.9	10.16	$1.815*10^{-8}$	3.5311	0.9	-2.99	37.65	$3.069*10^{-8}$	3.9816	**0.575**	-3.12	29.93	$8629*10^{-9}$	3.9416	0.687
Bahrain	-5.06	33.42	$1.692*10^{-7}$	4.642	0.58	-7.14	22.31	$2.022*10^{-8}$	4.0025	0.78	-6.14	42.14	$8.109*10^{-8}$	4.4525	**0.561**	-5.83	34.12	$5.423*10^{-8}$	4.2367	0.674
Iran	-1.94	7.13	$1.427*10^{-7}$	3.153	0.89	-1.34	17.74	$2.005*10^{-8}$	3.8214	0.82	-2.09	21.12	$4.429*10^{-8}$	3.4859	**0.741**	-2.34	27.96	$1.023*10^{-8}$	4.0593	0.691

DORSM: degree of resilience of stock market

Table 8. Analysis of different methods for evaluating resilience of stock markets

	Growth rate %*			Resilience calculation		
	2019	2020	2021	Main formula based on Figure 1-a	*CoVaR* coefficient based on Figure 1-b	Decreasing/Recovery trend coefficient using equation (9)
Saudi	0.83	-4.34	4.02	0.599	0.651	0.648
Qatar	0.99	-3.06	3.23	0.628	0.683	0.686
UAE	1.11	-4.96	3.07	0.560	0.601	0.59
Oman	-1.13	-3.38	3.26	0.647	0.719	0.707
Kuwait	-0.55	-8.86	1.15	0.524	0.584	0.562
Bahrain	2.17	-4.64	2.67	0.518	0.582	0.577
Iran	-3.07	3.33	4.72	0.681	0.748	0.765

* The growth rates are extracted from data.worldbank.org website.



(a) the general model without considering the source of shock

(b) the modified model with considering the source of shock by systemic risk

Figure 1. Resilience of the stock market

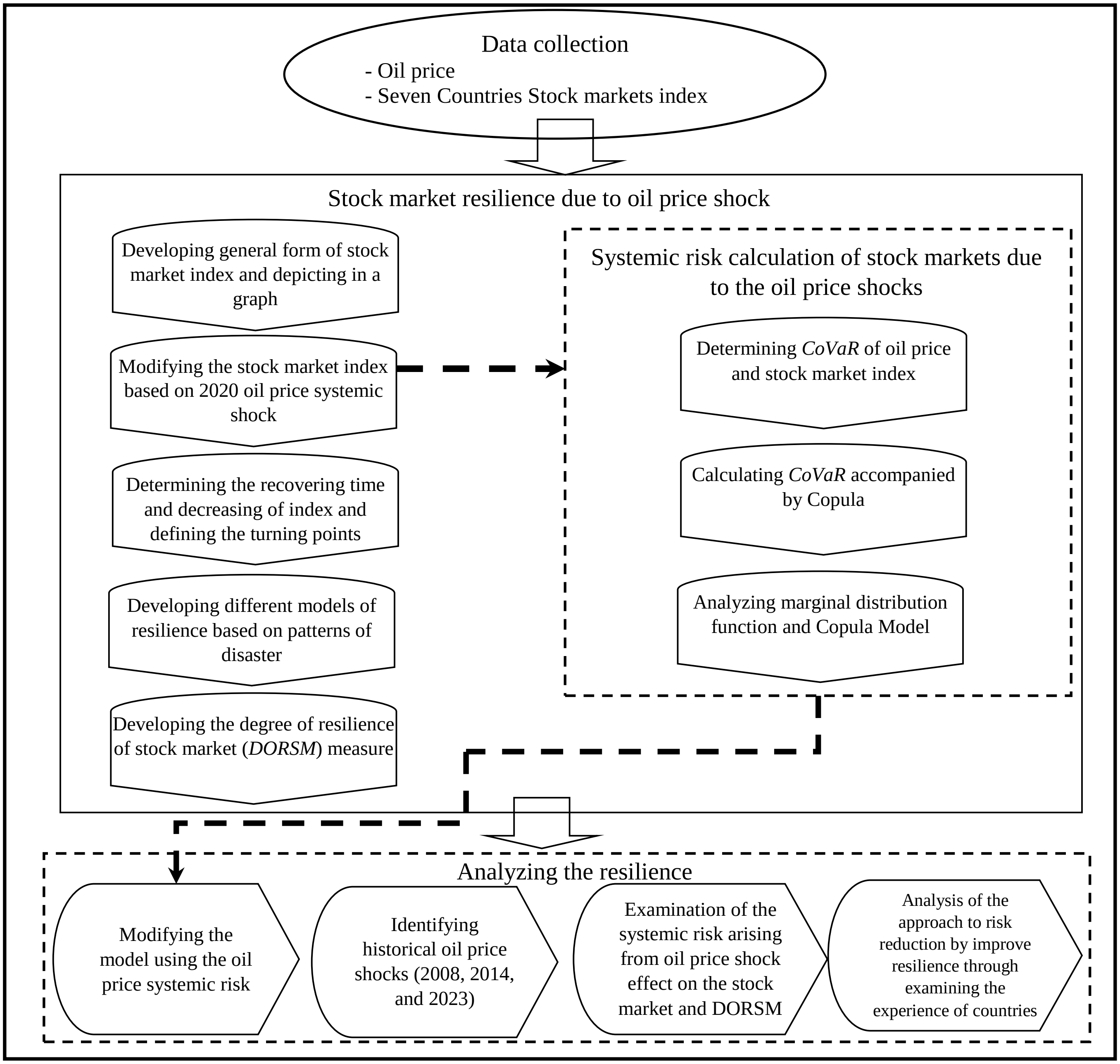


Figure 2. Flowchart of the proposed study

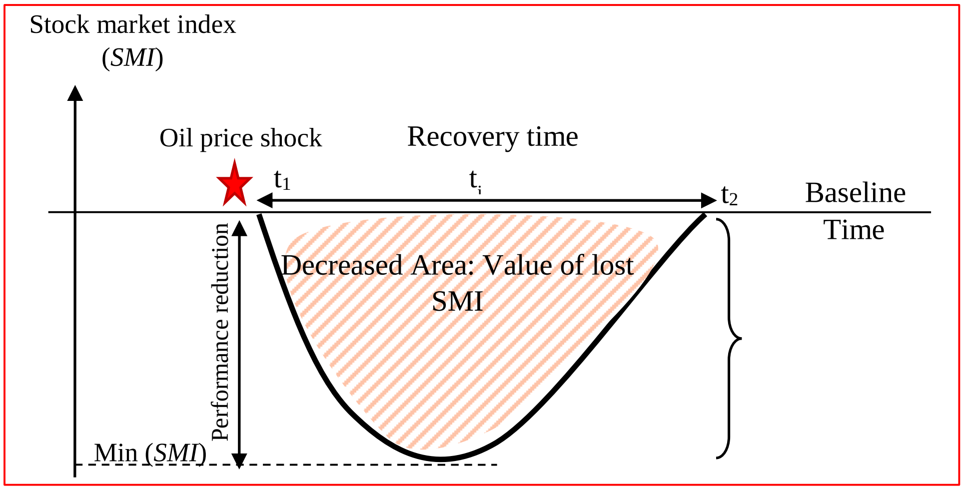


Figure 3. A schematic view of the *DORSM* function

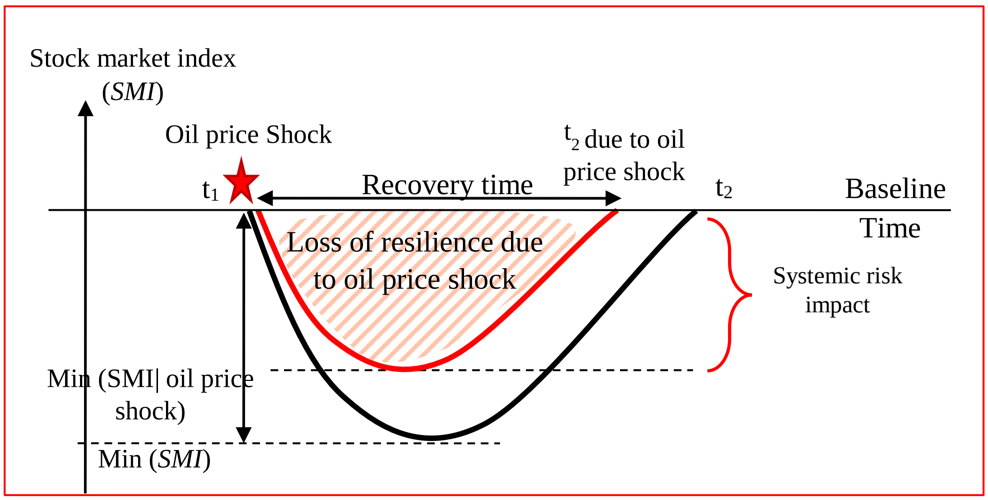


Figure 4. A schematic view of *DORSM* function based on oil price shock

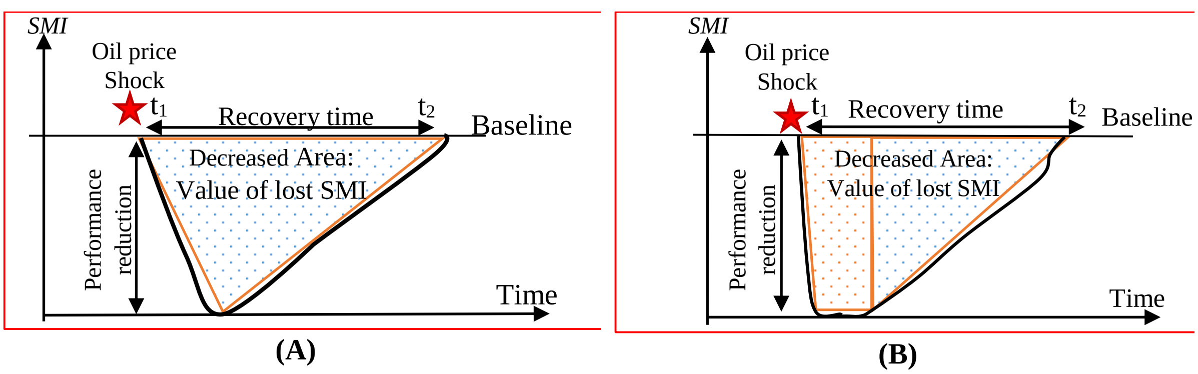


Figure 5. A schematic view of modified *DORSM*

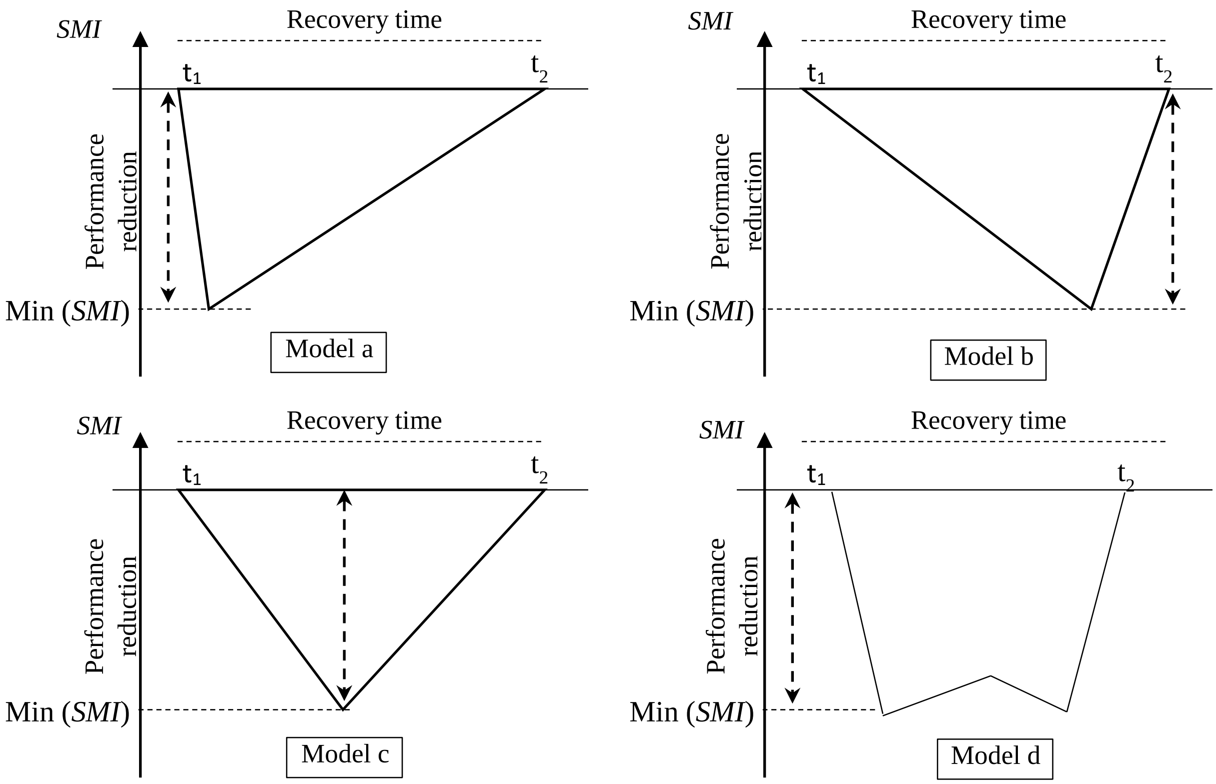


Figure 6. Basic models of Stock Market Index (*SMI*) trends

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