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# Study of Financial Distress Spillover Effect among Automobile Supply Chain Companies Listed in the Tehran Stock Exchange

Bita Delnavaz[a] , Mirfeiz Fallahshams[b,]*

[a] *Finance Department, Management Faculty, Central Tehran Branch, Islamic Azad University, Tehran, Iran*
[b] *Department of Business Management, Central Tehran Branch, Islamic Azad University, Tehran, Iran*

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ABSTRACT

This article investigates the financial distress spillover in automobile supply chain companies. For doing so, the distance to default of supply chain companies of Iran Khodro and SAIPA were calculated in time interval of 2013/11/28 to 2015/12/14 using time series KMV method. Then, the financial distress spillover in the supply chain companies of these two major automobile makers was tested in separated models using multivariate GARCH model. The results of the default probability of Iran Khodro companies showed that the default probability with pause of Khodro on the default probability of supply chain companies was significant and negative in 10% level. The results for SAIPA supply chain companies revealed that the default probability with a pause of Khaspa had an impact on the default probability of Kesapa, Pask and Khazin in significance level of 10%.

## 1 Introduction

The financial crisis of 2007, which according to many experts, is one of the biggest crises in the world after 1930s affected not only the American economy but also many economies. Therefore, it has been likened to a huge tsunami that began in the United States and transmitted with expanding its scope to European countries and then other countries in the world and in the meantime, influenced even the economies of the small countries. Following this crisis, the economic witnessed the bankruptcy of various financial institutions and buying of the companies by the government or competing companies. Price index in large and small stock exchanges faced a significant decline. Lending power and the liquidity provided to financial institutions fell sharply. By continuation of crisis in the real economic sector, the economic growth reduced and unemployment increased [1]. One of the issues that can aid in the decision-making process oninvestment is existence of the right tools and models for assessment of financial conditions of organizations. As one of the most important tools, it can be referred to predicting models of the company's financial distress. From the financial point of view, financial distress can be interpreted as company loss. In this case, the company is likely to be in financial crisis and suffers from bankruptcy. Most financial distress models have examined its effects on financial assets and finaical

* Corresponding author. Tel.: +98 9123890554
E-mail address: *: fallahshams@gmail.com*

claims of the company [2, 3, 4]. However, little research has examined the effect of a company's bankruptcy volitality on other companies. Early empirical studies of bankruptcy volitlaity have focused on the corporate financial distress spillover on stock prices of competing firms [5]. Theoretically, when a company is bankrupted, its liquidation and dissolution will affect the local economic. The reason for the financial crisis spillover from one bankrupted company to another is due to the business exchanges among companies. Each company is dependent on other companies to supply raw materials, finance and selling their products and services. As a result, the interdependence of companies causes bankruptcy to spread from one company to another [6]. Given the multiplicity of companies in different countries that are in financial distress and consequently bankruptcy and its effects on other companies, conducting research on the ways to predict such situations as well as their effects seems essential. This study examines the extent of financial distress spillover in automobile supply chain companies.

Therefore, according to the reaserch on bankruptcy spillover among companies, it can be argued that when supply chain companies are in a state of crisis or financial distress (high default probability), this financial distress spreads to other companies and most likely they suffer from crisis or even financial distress. The effect of liqudation information of the bankrupted companies on the index of different industries was investigated through regression panel in [7]. Using this model in the Iranian stock exchange requires liqudation information from bankrupted companies. Therefore, due to the lack of this information, it is necessary to calculate the probability of financial distress of the automobile supply chain companies using an appropriate model. The KMV model has been used as a predictor of corporate bankruptcy for predicting distance to default in [8]. Multivariate GARCH approach has also been used in most studies to investigate the volatility and risk spillover [9]. Therefore, in this research, first, based on the time series of returns of automobile supply chain companies and using KMV method, the default probability is calculated. Then, using DCC stipulation of multivariate GARC model, the financial distress spillover among automobile supply chain companies is examined and tested.

## 2 Review of Literature

### 2.1 Financial Distress and Bankruptcy

Corporate and financial distress have always been a major concern for creditors, investors and governments, so that timely identification of companies encountering financial distress can partly prevent potential losses to stakeholders. Companies need sufficient resources to continue their business. If the company does not have sufficient resources to meet its needs and fulfill its obligations, it will suffer financial distress. The factors that lead to the financial distress of a company do not appear overnight. Signs of a company's financial distress appear much earlier than the eventual bankruptcy. A financial crisis is a situation in which a company is unable to obtain sufficient financial resources to continue its operations and has difficulty in doing its job [10]. The resreachers have considered financial distress as a situation where the firm's cash flows are less than the sum of its long-term debt interest expense. In times of financial distress, companies face two major problems: lack of liquidity in meeting their overdue obligations and decrease in profitability. In other words, in times of financial distress, cash flows do not provide the necessary coverage to meet obligations and the company becomes temporarily unable to pay its debts. In this case, companies are selling assets and getting loans, which results in reduced capacity and production performance as well as increased leverage.

Altman and Hotchkiss [8] suggest that financial distress occurs when the rate of return realized for the capital in the firm is significantly and consistently below the expected rate of return. Bankruptcy is a

legal and financial situation for a firm with financial distress. A company may be distressed for a long time, but because there is no legal prohibition so that the company is not considered bankrupted.
There are many reasons for companies to be distressed. The most important causes of corporate financial distress are corporate mismanagement. Managerial mistakes, high cost, financing, ineffective sales activities and financial crisis and recession, onset of the downturn in the company's product lifecycle, high cost of production can alone or in combination be a warning of corporate bankruptcy. Economic activities can be another reason for bankruptcy of companies. Recession, interest rate changes, rising inflation, raw material price fluctuations and international economic conditions are the economic causes of bankruptcy. Government decisions, unintended natural consequences and the life span of organizations are other causes of bankruptcy [9].

## 2.2 Impact of Splliover

Spillover refers to situations in which the volatility of a market or a corporate will have an indirect adverse effect on the returns and volatility of the markets and other firms. The convergence and financial dependency between markets and firms causes volatility risk between them [10]. The volatility spillover between financial markets and firms indicates the process of transferring information among them. Since financial markets are interconnected, information created in one market can affect other markets and firms [11]. The risk of a financial system is greater than the total risk of individual firms in that financial system. The reason is the effectiveness of risk-sharing among firms [12].

## 2.3 Research Bakground

The studies on the business financial distress spillover can be divided into two general groups:
Group one: The studies that investigate financial distress spillover among competitor businesses:
This studies mainly emphasize the impact of bankruptcy of a business on other competitors. Stloze and Lung [5] found that announcement of bankruptcy has a negative impact on the competitor stock price. However, the reserachers showed that announcement of bankruptcy increases other companies debtes rate [13]. The results of suggested that the debt securities are enhanced when the industry competitors are suffering from bankruptcy. The results showed that non-bankrupted competitors are influenced by the rivals' bankruptcy. The second group of studies investigating the impact on the suppliers and customers of the business is less than first group studies. The crisis spillover in the supply chain is unfamiliar affair. For instance, the potential impact of GM bankruptcy on the suppliers was so important for the federal government that 5 milliard dollars were allocated for protection of the items supplier companies. In a poll conducted by the Times, 68% of the supplier companies' managers announced that if GM announce bankruptcy, its companies should reduce their size. However, all suppliers and customers of the bankrupted company were not affected. Among, 49 GM main suppliers, the collective return of 5 days for crisis period varied from -17% to + 24%. Various channels have been proposed for being influence of supply chain of a business. The first channel is related to change of the business approach for importing middle input from foreign countries in order to increase compatibility. In this case, the domestic suppliers' performance and profitability have been affected significantly [14]. The second channel depicts the financial distress spillover by high default probability of the customers that can increase the distress risk in the suppliers. If the business main customers suffer from distress, the payments will be encounter with delay or their trading credit is jeopardized. When a customer is bankrupted, due to uncertainty in finding new customers, the supplier might be unable to regain the selling

market completely [15]. Baur and Lucey [16] suggested that it is expected that the suppliers and customers of the specific products producers have been affected seriously by distress of one of the supply chain members. Also, Cochran et al. [17] Showed a negative impact of financial distress of a business on the stock price of suppliers. When the firms encounter with uncertainty in accessibility on inputs, they might be decided on vertical merge during supply chain [18]. A research on examining the relationship between bankruptcy of the banks and its impact on companies' bankruptcy and showed that banks are considered as the most important factor for using a working optimal system for the companies [19]. Engle and Kroner [20] suggested that the probability of rescue of a business that suffers from economic problems is less than the business suffering from financial perspective (high leverage but profitable). In spite of numerous studies in financial distress scope, none of the national and international studies have been investigated the financial distress spillover using Multivariate GARCH model. Wadecki et al [21] finds that the subsidy the manufacturers provide to their distressed suppliers depends on the supply chain structure. Our paper also shows that supply chain interactions play an important role in the profitability of all firms in the supply chain both before and after bankruptcy.
The resreachers have explores the spillover effects of reorganization and liquidation on geographically proximate firms [22]. They exploit the random assignment of bankruptcy judges as a source of exogenous variation in the probability of liquidation. They find that employment declines substantially in the immediate neighborhood of the liquidated establishments, relative to reorganized establishments. The spillover effects are highly localized and concentrate in nontradable and service sectors, consistent with a reduction in local consumer traffic and a decline in knowledge spillovers between firms. The evidence highlights the externalities that bankruptcy design can impose on nonbankrupt firms.

## 3 Methodology

In this article, according to the subject and nature of the data, descriptive-correlation analysis and regression method has been used. At first, based on stock price data of Iran Khodro and SAIPA supply chain companies, using time series models, a model was estimated for expected return of each company and then, through KMV model, the distances to default were calculated during implemention of obligations. Then, through the MGARCH-DCC model, the financial distress among automobile supply chain companies was investigated in Iran Khodro Group companies and SAIPA Group companies.

### 3.1 KMV Model for Calculation of Distance to Default

The main assumption of KMV models is that default occurs when the value of the company's assets is not sufficient to repay the company's debt. In Merton's original model, the company' debt consists of a single non-coupon bond with nominal value of L and maturity T. No payment is made before time T and the shareholders wait until time T and then they decide on default or repayment of the debt. Accordingly, the default probability is meant that at time T, the value of the assets is less than the value of the debt. The value of company' debt can be determined through its balance sheet [23]. In order to calculate the default probability, it is essential to determine the distribution of the value of the assets at maturity [24]. In the credit risk literature, the term "distance to default" (DD) is used which indicates the number of standard deviations that the expected value of the asset at maturity ($A_T$) has from the point of distance default [25].
So it can be written:

$$DD = \frac{\ln A_t + \left(\mu - \frac{\sigma}{2}\right)(T-t) - \ln L}{\sigma\sqrt{T-t}} \quad (1)$$

Where$A_t$ is the value of the assets market at time t, L is the value of debts at t, μ is the momentum rate and σ is theasset value logarithm annual fluctuations. Because the market value of the company's assets is not directly visible therefore, the value of $A_t$must be calculated to put in the above equation. In addition, the standard deviation of assets value is also unknown. If we assume that the company does not pay dividends, the stock value will be determinedusing the Black-Scholes formula for pricing buying options:

$$E_t = A_t . \varphi(d_1) - Le^{-r(T-t)}\varphi(d_2) \quad (2)$$

That

$$d_1 = \frac{\ln\frac{A_t}{L} + \left(r + \frac{\sigma^2}{2}\right)(T-t}{\sigma\sqrt{T-t}} \quad (3)$$

$$d_2 = d_1 - \sigma\sqrt{T-t}$$

Where r represents a risk-free rate of return and Φ depicts a cumulative normal distribution. Calculation of the value of $A_t$ and standard deviation of the value of assets from the above formula is difficult given the fact that we have just one equation with two unknowns. There are several ways to solve this equation and we use the "repetition" method. Stock prices of each company were considered in the study period for 260 trading days in 2016. Stock price time series, along with total market index, number of shares in the hands of shareholders, the amount of debt and the risk-free rate of return were considered as the model input. Then distance to default and default probability were calculated from this method. Distance to default values and default probability of each company for one-year period was calculated in 2016.

## 3.2 Research Variables

The main variable of the research is to investigate the financial distress spillover among automobile supply chain companies as distance to default. As stated, the values of the companies' distance to default are calculated using data on asset values, liabilities, standard deviation of return on assets through the KMV model in the research domain.

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## 3.3 The MGARCH-DCC Model for the Financial Distress Spillover

The DCC model is introduced by Engle [20] to capture the dynamic time-varying behavior of conditional covariance. DCC model has been used in some papers to examine the volatility spillover across different stock markets. The DCC-MGARCH model is a dynamic model with time-varying mean [26], variance and covariance of roturnscricsr$_{i,t}$ for stock *i* at time *t*, with the following equations:

$$r_{i,t} = \mu_t + \varepsilon_t, \quad \mu_t = E(r_{it}/\psi_{t-1}) \text{ and } \varepsilon_t/\psi_{t-1} \sim N(O,H_t) \tag{4}$$

Where ψt-1 indicates the set of information available at time t-1. The conditional variance-covariance matrix, ,$H_t$, can be constructed by the following equations:

$$H_t = D_t R_t D_t \tag{5}$$

$D_t = \text{diag}\left(h_{11,t}^{1/2} \ldots h_{NN,t}^{1/2}\right)$ is a diagonal matrix of square root conditional variances. $h_{i,t}$ can be defined as $h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-i}^{2} + \beta^{h_{i,t-1}}{}_i$., where $\omega_i$ is a constant term and $\alpha_i$ is the ARCH effect and $\beta_i$ is the GARCH effect. $R_i$ is a time-varying conditional correlation matrix and it is stated as follows:

$$R_t = diag\left(q_{11,t}^{-1/2} \ldots q_{NN,t}^{-1/2}\right)\overline{Q_t}\, diag\left(q_{11,t}^{-1/2} \ldots q_{NN,t}^{-1/2}\right) \tag{6}$$

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha\mu_{t-1}\mu_{t-1} + \beta Q_{t-1} \tag{7}$$

Where $\mu_t^{*} = diag(Q_t)^{1/2}\mu_t$, with $Q$ the unconditional correlation matrix of $\mu_{t-1}^{*}$. $\alpha$ And $\beta$ are nonnegative scalar parameters. If the value of $\alpha + \beta$ is close to one, this indicates high persistence in the conditional variance

The correlation estimator is $P_{ij,t} = \left(\frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}\right)$ (8)

Nowadays, multivariate models are mostly used to model the dynamics of returns. Use ofmultivariate time series models has two important features. Firstly,they are very effective in identifying the relationship between the series, secondly, they increase the accuracy of predictions [27]. For example, if the past values of a series affects the other series, it is better to use multivariate models. However, use of systemic or multivariate models have two important constraints. First, whatever the estimated parameters are increased the accuracy of the results will be reduced and for the reliability of the results, we need more data. Second, in many cases, the results have no great explanation power. So we usually search for simile structures [28]. In multivariate GARCH models, the number of parameters increases significantly with increase of the model dimension and on the other hand, it is necessary that the matrix of variance is definitely positive. Setting these features by estimated parameters are not so simple [29]. In the CCC model the conditional coefficient as follows:

$$R = \begin{bmatrix} 1 & \ldots & \rho_{1N} \\ \ldots & \ldots & \ldots \\ \rho_{1N} & \ldots & 1 \end{bmatrix} \tag{9}$$

Where $\rho_{ij}$ is the coefficient between variables i and j. Considering constant of the conditional coefficients reduced the parameters production and as a result estimation has become simple. Under this condition, $H_t$ as conditional variable matrix is expressed as follows:

$$H_t = \text{diag}\left(\sqrt{h_{11,t}}, \ldots, \sqrt{h_{nn,t}}\right)[R]\ \text{diag}\left(\sqrt{h_{11,t}}, \ldots, \sqrt{h_{nn,t}}\right) \tag{10}$$

In the case with variables (N=20 and p=q=1, the expanded state of matrix $H_t$is as follows. The operator diag chooses the elements on the matrix diameter.

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix}\begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix}\begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \tag{11}$$

Where variances, $h_{11,t}$ and $h_{22,t}$ are the multivariate GARCH with p=q=1. In 2002, Engle did not consider the assumption being constant of the conditional coefficient and proposed DCC called dynamic coefficient model. In this model allowed the coefficient matrix to change. In definition of matrix $H_t$, there is no difference model DCC and CCC and in this model, matrix $H_t$, is also called variance-covariance matrix.

$$H_t = D_t \, R_t \, D_t \tag{12}$$

Engel considered two different estimation for $R_t$ that in the first estimation, the rate exponential form is used as follows:

$$Q_t \; (1-\lambda)\,(\varepsilon_{t-1} - \varepsilon_{t-1}) + \lambda \, Q_{t-1} \tag{13}$$

Where $Q_t$ is a definition of positive and unlimited matrix and $R_t$ is defined as follows:

$$R_t = \operatorname{diag}(Q_t)^{-1/2} \, Q_t \, \operatorname{diag}(Q_t)^{-1/2} \tag{14}$$

Other form of model GARCH (1,1) is considered as an indicator for defining the model:

$$Q_t = R_0 \, (1-\alpha-\beta) + \alpha \, (\varepsilon_{t-1} \, \varepsilon'_{t-1}) + \beta Q_{\,t-1} \tag{15}$$

Where R.unconditional correlation matrix and the condition of $\alpha+\beta<1$ is established. In general statement, we have:

$$\begin{aligned}
& r_t \mid \psi_{t-1} \sim N(o, D_t R_t D_t) \\
& \varepsilon_t = D_t^{-1} r_t \\
& D_t^2 = \operatorname{diag}(a_{0,t}) + \operatorname{diag}(a_{1,i}) \, o r_{t-1} \, r'_{t-1} + \operatorname{diag}(b_{l,i}) \, o D_{t-1}^2 \\
& Q_t = R_0 \, (1-\alpha-\beta) + \alpha \, (\varepsilon_{t-1}\varepsilon'_{t-1}) + \beta \, Q_{t-1} \\
& R_t = \operatorname{diag}(Q_t)^{-1/2} \, Q_t \, \operatorname{diag}(Q_t)^{-1/2}
\end{aligned} \tag{16}$$

This approach caused to a general confirmation of model DCC as above relations. It is clear that $r_t$ and return rate and return $r_t|\psi_{t-1}$ are according to the condition of previous period information.

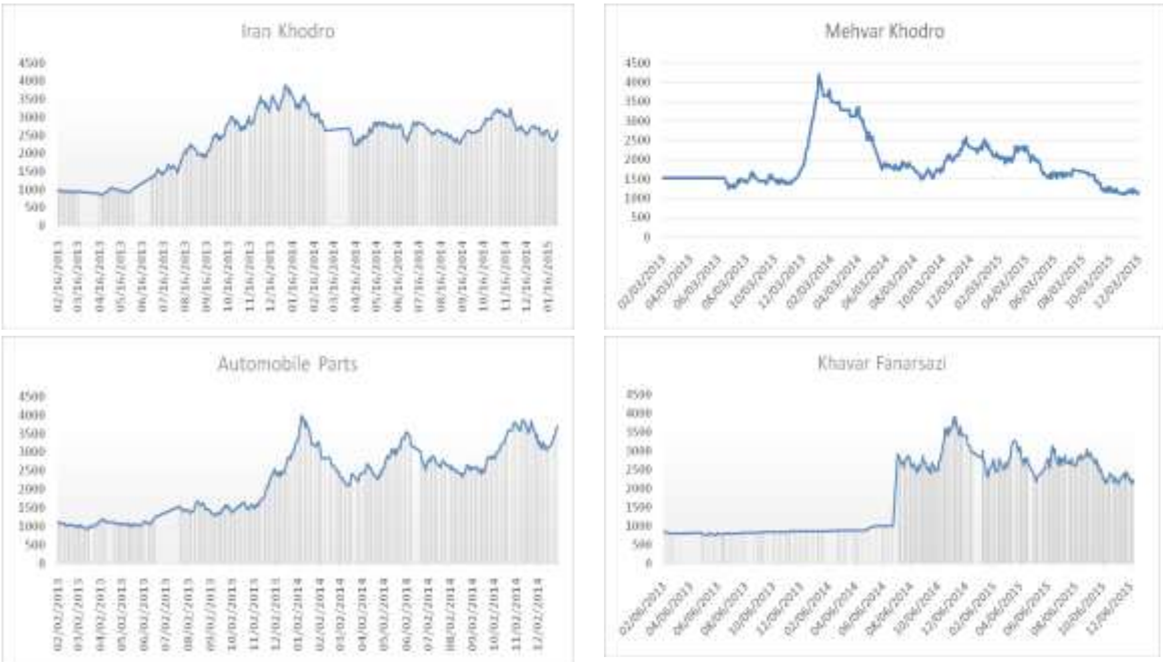


**Fig. 1:** The Stock Price of Iran Khodro Supply Chain Companies Since 17.02.2013 to 14.12.2015
Source: Rahavardnovin Software


**Fig. 2:** The Stock Price of SAIPA Supply Chain Companies Since 17.02.2013 to 14.12.2015
Source: Rahavardnovin Software

**Table 1:** Descriptive Statistics of the Iran Khodro and SAIPA Supply Chain Companies Return, Probability of Default and Distance to Default

| | | **Iran Khodro** | | | **SAIPA** | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **Explanation** | **Khtogha** | **Khfanar** | **Khodro** | **Khosaz** | **Khazin** | **Khsapa** | **Plask** | **Kesapa** |
| Return | Mean | 0.0015 | 0.0025 | 0.0019 | 0.0013 | 0.00553 | 0.0033 | 0.0008 | 0.0014 |
| | Mode | -0.0001 | 0.0000 | -0.0003 | 0.0000 | 0.002 | 0.00073 | 0.00003 | 0.00153 |
| | SD | 0.0363 | 0.0552 | 0.0372 | 0.0442 | 0.0629 | 0.040 | 0.0361 | 0.0195 |
| | Skewness | 0.8593 | 12.2533 | 1.58983 | -6.3654 | 9.2573 | 2.0423 | 1.3720 | -0.2659 |
| | Slenderness | 12.544 | 243.28 | 24.563 | 112.80 | 161.71 | 24.443 | 9.6208 | 6.0582 |
| | Jargue-Bera | 2617 | 1623 | 1322 | 3400 | 576613 | 10760 | 1160 | 217 |
| | Probability | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| probability of default(PD) | Mean | 0.000 | 0.000 | 0.001 | 0.006 | 0.014 | 0.002 | 0.001 | 0.000 |
| | Mode | 0.000 | 0.000 | 0.000 | 0.003 | 0.014 | 0.002 | 0.001 | 0.000 |
| | SD | 0.000 | 0.000 | 0.001 | 0.009 | 0.005 | 0.001 | 0.001 | 0.000 |
| | Skewness | 2.859 | 2.068 | 3.192 | 4.300 | 0.646 | -0.045 | 1.499 | 1.747 |
| | Slenderness | 11.772 | 6.793 | 14.307 | 20.710 | 3.039 | 2.020 | 5.901 | 6.284 |
| | Jargue-Bera | 456.899 | 131.216 | 702.505 | 1614.935 | 9.618 | 5.568 | 100.069 | 132.212 |
| | Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.008 | 0.062 | 0.000 | 0.000 |
| distance to default (DD) | Mean | 6.8905 | 4.7488 | 3.3809 | 2.6764 | 3.194 | 3.025 | 3.194 | 5.459 |
| | Mode | 6.9000 | 4.8000 | 3.3485 | 2.6984 | 3.170 | 2.921 | 3.170 | 5.470 |
| | SD | 0.1664 | 0.2410 | 0.2878 | 0.2889 | 0.203 | 0.293 | 0.203 | 0.124 |
| | Skewness | -0.3243 | -0.3466 | 0.2766 | -1.2782 | -0.106 | 1.043 | -0.106 | 0.296 |
| | Slenderness | 2.8301 | 2.2465 | 3.2845 | 6.6905 | 2.092 | 2.830 | 2.092 | 3.876 |
| | Jargue-Bera | 1.8730 | 4.3681 | 1.6123 | 83.9824 | 4.999 | 25.192 | 4.999 | 6.429 |
| | Probability | 0.3920 | 0.1126 | 0.4466 | 0.0000 | 0.082 | 0.000 | 0.082 | 0.040 |

### 3.4 Data and Data Collection Method

The time series of stock prices, together with the total market index, number of stocks in the hands of shareholders, the amount of debt and the risk-free rate of return are the data of this research. The data were extracted from Tehran Stock Exchange Technology Company, Tehran Stock Exchange Publishers' Comprehensive Information System, and Rahavard-e-Novin software in the time interval of the current research period since 2013/2/16 to 2015/12/14. In this research, Iran Khodro automobile supply chain companies and SAIPA were separately investigated. For this purpose, except for the symbol of the main companies (Iran Khodro and SAIPA) another supply chain companies were chosen. For Iran Khodro supply chain, Iran Khodro, AutomobileParts Supply Company, MehvarSazan and Khavar Spring Manufacturer Company with the symbol of the Khdro, Khatogha, Khosaz and Khafanar in the Tehran Stock Exchange were also selected. Also for the companies of SIPA supply chain, the companies of SAIPA, Plascokar, SAIPA Azin and SAIPA Shishe with symbols of Kesapa, Plask, Khazin and Kesapa have been selected. The share of these companies is depicted in the following diagrams.

## 4 Findings

Table 1 summarizes the descriptive statistics for Iran Khodro and SAIPA supply chain companies. As it is seen, the average daily return of all companies is positive; however, in the Iran Khodro supply chain, Khafnar has the highest average return and khosaz has the lowest average return. Also in the SAIPA supply chain, Khazin has the highest average return and Plask has lowest average return during research period. Standard deviation in the table shows that the fluctuations in the companies with higher average return are more than other companies. Also the results of the Jarque-Bera statistics depict rejection of the null hypothesis of normal distribution for all return series. Also, the examination of the results of the unit root tests forIran khodro and SAIPA supply chain companies show that the price return of these companies is durable in 1% level.

**Table 2:** The Results of Durably Test in the Iran Khodro and SAIPA Supply Chain Companies Distance to Default

| Explanation | Iran Khodor | | | SAIPA | | | |
|---|---|---|---|---|---|---|---|
| | **Khosaz** | **Khodro** | **Khfanar** | **Khtogha** | **Plask** | **Khsapa** | **Khazin** |
| **ADF** | -23.83 | -24.4 | -19.4 | -24.4 | -25.07 | -22.09 | -26.0 |
| **Prob** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| **PP** | -23.8 | -24.43 | -22.54 | -24.43 | -24.89 | -28.31 | -26.11 |
| **Prob** | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

The results of Ljung-Box test for testing hypothesis of the research providing inexistence of correlation for the model remainder depicted lack of rejection of null hypothesis and in other word, nonexistence of self-correlation for remainders in all models. The statistical Tables for this test are shown for all estimated models in part (c) of the Tables.

### 4.1 Relationship of the Automobile Supply Chain Companies' Financial Distress

In order to investigate the financial distress of supply chain companies, MGARCH-DCC model was used. For this purpose, first, using self-regression vector model (VAR) to determine the distance to default of supply chain companies of both groups of companies and then based on the MGARCH-DCC model, the financial distress among supply chain companies was investigated.

**Table 3:** DCC Model Estimation Results

| | **Coefficient** | **Probe** |
|---|---|---|
| C(1) | 0.000 | 0.021 |
| C(2) | 0.001 | 0.000 |
| C(3) | 0.000 | 0.084 |
| C(4) | 0.000 | 0.019 |
| A(1) | 0.191 | 0.000 |
| A(2) | -0.001 | 0.000 |
| A(3) | 0.190 | 0.047 |
| A(4) | 0.178 | 0.000 |
| B(1) | 0.699 | 0.000 |
| B(2) | 0.263 | 0.000 |
| B(3) | 0.734 | 0.000 |
| B(4) | 0.789 | 0.000 |
| a | 0.017 | 0.057 |
| b | 0.491 | 0.000 |
| Shape | 3.841 | 0.000 |

### 4.1.1 Relationship of the Financial Distress in the SAIPA Supply Chain Companies

The results of the durability test of default probability of SAIPA supply chain companies showed that the default probability of these companies is not durable at 5% level. However, by a differential, this variable becomes durable. Thus, the first order deferential, these time series are used in VAR model. The results of durability test are shown in the appendix. Also to select a pause optimal model, SIC statistics has been used. The VAR(1)-DCC model results are given in the table below.

**VAR(1)-DCC Model Estimation Results for SAIPA Supply Chain:**

a) VAR(1) model estimation results

$$\begin{bmatrix} kesapa_t \\ khazin_t \\ khsapa_t \\ plsk_t \end{bmatrix} = \begin{bmatrix} \underset{(0.01)}{0.00} \\ \underset{(0.02)}{0.00} \\ \underset{(0.00)}{0.002} \\ \underset{(0.02)}{0.001} \end{bmatrix} + \begin{bmatrix} \underset{(0.27)}{-0.08} & \underset{(0.03)}{1.46} & \underset{(0.06)}{-0.20} & \underset{(0.13)}{-0.50} \\ \underset{(0.77)}{0.01} & \underset{(0.12)}{-0.20} & \underset{(0.59)}{-0.01} & \underset{(0.00)}{0.15} \\ \underset{(0.00)}{0.04} & \underset{(0.00)}{0.73} & \underset{(0.03)}{-0.1} & \underset{(0.07)}{-0.1} \\ \underset{(0.62)}{0.02} & \underset{(0.01)}{0.67} & \underset{(0.66)}{-0.02} & \underset{(0.06)}{-0.21} \end{bmatrix} \times \begin{bmatrix} kesapa_{t-1} \\ khazin_{t-1} \\ khsapa_{t-1} \\ plsk_{t-1} \end{bmatrix}$$

b) DCC Model Estimation Results

$$H_{ii}\,(t)=c_i+\alpha_i\,u_i^2\,(t-1)+b_iH_{ii}\,(t-1)$$
$$Q_l=(1-\alpha-b)\,Q_0+\alpha\,u_{r-1}\,u'_{-1}+b\,Q_{r-1}$$
$$\mathrm{H_{ij}}\,(\mathrm{t})=\mathrm{Q_{ij}}\,(\mathrm{t})\,\sqrt{\mathrm{H_{ii}}\,(\mathrm{t})\,\mathrm{H_{jj}}(\mathrm{t})}\,/\,\sqrt{\mathrm{Q_{ii}}(\mathrm{t})\,\mathrm{Q_{jj}}\,(\mathrm{t})}$$

c) Test Results

**Table 4:** result *ofo* of Ljung-Box Test

| **Results of Ljung-Box** | **Kesapa** | **Khazin** | **Khsapa** | **Plask** |
|---|---|---|---|---|
| Q(4) | 3.36(0.49) | 4.28(0.36) | 4.15(0.38) | 2.63(0.62) |
| $Q^2(4)$ | 9.59(0.05) | 5.09(0.27) | 1.50(0.82) | 7.70(0.10) |

- The values in the parenthesis depict P-Value

As you see in section (a) in the above table, the results of the estimation of the VAR model reveal that the default probability with pause in the Khazin and Kesapa on the SAIPA default probability is positive and significant in confidence level 1% and it depicts that SAIPA default probability is affected by its supply chain companies. Also, the results of model VAR showed that the financial distress probability with pause of Khaspa on the financial distress probability of supply chain companies Kesapa, Plask and Khazin is significant and negative in 10% level. This indicates that the performance and profitability of domestic automobile parts suppliers will be strongly influenced by the performance of the original company. And as a result of the financial distress of the parent company, automobile parts companies will also be distressed. The results of the DCC model estimation are shown in section b of the table. As you can see, all the coefficients of vectors A and B are significant at the 5% level.
This shows that the bankruptcy risk of the major automobile maker, SAIPA, is transmitted to automobile parts companies. The coefficients α and β are also significant at the 5% level, indicating a correct estimation of the DCC model. The results of the Ljung-Box test with the null hypothesis of no correlation for the residuals and the second residual power are presented in the third part indicating that the null hypothesis of zero correlations between the residuals and the second residual power is rejected and thus the model is correct.

$$\begin{bmatrix}\mathrm{khtogha}_t\\ \mathrm{khfanar}_t\\ \mathrm{khodro}_t\\ \mathrm{khosaz}_t\end{bmatrix}=\begin{bmatrix}0.04\\ \scriptstyle(0.14)\\ 0.03\\ \scriptstyle(0.14)\\ 0.03\\ \scriptstyle(0.13)\\ 0.009\\ \scriptstyle(0.00)\end{bmatrix}+\begin{bmatrix}0.21 & 0.03 & -0.33 & -0.60\\ \scriptstyle(0.00) & \scriptstyle(0.70) & \scriptstyle(0.01) & \scriptstyle(0.00)\\ 0.22 & -0.23 & -0.21 & -0.21\\ \scriptstyle(0.00) & \scriptstyle(0.00) & \scriptstyle(0.14) & \scriptstyle(0.07)\\ 0.01 & 0.05 & 0.17 & -0.31\\ \scriptstyle(0.07) & \scriptstyle(0.03) & \scriptstyle(0.03) & \scriptstyle(0.00)\\ 0.03 & -0.02 & -0.01 & -0.04\\ \scriptstyle(0.14) & \scriptstyle(0.48) & \scriptstyle(0.78) & \scriptstyle(0.43)\end{bmatrix}\times\begin{bmatrix}\mathrm{khtogha}_{t-1}\\ \mathrm{khfanar}_{t-1}\\ \mathrm{khodro}_{t-1}\\ \mathrm{khosaz}_{t-1}\end{bmatrix}$$

### 4.1.2 Relationship of Financial Distress in Iran Khodro Supply Chain Companies

The results of the durability test of default probability of Iran Khodro supply chain companies showed that the default probability of these companies is not durable at 5% level. However, by a differential, this variable becomes durable. Thus, the first order deferential, these time series are used in VAR model. The results of durability test are shown in the appendix. Also to select a pause optimal model, SIC statistics has been used. The VAR (1)-DCC model results are given in Table 5.

**Table 5:** DCC Model Estimation Results

| | **Coefficient** | **Probe** |
|---|---|---|
| C(1) | 0.000 | 0.021 |
| C(2) | 0.001 | 0.000 |
| C(3) | 0.000 | 0.084 |
| C(4) | 0.000 | 0.019 |
| A(1) | 0.191 | 0.000 |
| A(2) | -0.001 | 0.000 |
| A(3) | 0.190 | 0.047 |
| A(4) | 0.178 | 0.000 |
| B(1) | 0.699 | 0.000 |
| B(2) | 0.263 | 0.000 |
| B(3) | 0.734 | 0.000 |
| B(4) | 0.789 | 0.000 |
| a | 0.017 | 0.057 |
| b | 0.491 | 0.000 |
| Shape | 3.841 | 0.000 |

**VAR(1)-DCC Model Estimation Results for Iran Khodro Supply Chain**

a) VAR(1) model estimation results

$$\mathrm{H}_{\mathrm{ij}}(\mathrm{t}) = \mathrm{Q}_{\mathrm{ij}}(\mathrm{t})\sqrt{\mathrm{H}_{\mathrm{ii}}(\mathrm{t})\,\mathrm{H}_{\mathrm{jj}}(\mathrm{t})}\,/\,\sqrt{\mathrm{Q}_{\mathrm{ii}}(\mathrm{t})\,\mathrm{Q}_{\mathrm{jj}}(\mathrm{t})}$$

b) DCC model estimation results

$$H_{ii}(t) = c_i + \alpha_i\, u_i^2(t-1) + b_i H_{ii}(t-1)$$
$$Q_l = (1-\alpha-b)\,Q_0 + \alpha\, u_{r-1}\, u'_{-1} + b\, Q_{r-1}$$
$$\mathrm{H}_{\mathrm{ij}}(\mathrm{t}) = \mathrm{Q}_{\mathrm{ij}}(\mathrm{t})\sqrt{\mathrm{H}_{\mathrm{ii}}(\mathrm{t})\,\mathrm{H}_{\mathrm{jj}}(\mathrm{t})}\,/\,\sqrt{\mathrm{Q}_{\mathrm{ii}}(\mathrm{t})\,\mathrm{Q}_{\mathrm{jj}}(\mathrm{t})}$$

c) Tests Results

**Table 6:** result *ofo* of Ljung-Box Test

| **Results of Ljung-Box** | **Khtogha** | **khfanar** | **Khodro** | **Khosaz** |
|---|---|---|---|---|
| Q(4) | 4.28(0.36) | 3.34(0.48) | 4.15(0.38) | 4.63(0.30) |
| $Q^2(4)$ | 8.52(0.06) | 5.29(0.31) | 1.83(0.75) | 2.18(0.62) |

- The values in the parenthesis depict P-Value

As you see in section (a) in the above table, the results of the estimation of the VAR model reveal that the default probability with pause in the Khatogha, Khafanar and Khosaz have affected the Iran Khodro-default probability and this relationship between the return and the return spillover of the Iran Khodro supply chain companies proposed in the previous section was observed. The results of the default probability of Iran Khodro companies showed that the default probability with pause of Khodro on the default probability of supply chain companies (Khatuga, Khafnar and Khosaz) was significant and negative in 10% level.

This indicates that the performance and profitability of domestic automobile parts suppliers will be strongly influenced by the performance of the original automobile maker. And as a result of the financial distress of the parent company, automobile parts companies will also be distressed. The results of the DCC model estimation are shown in section b of the table. As you can see, all the coefficients of vectors A and B are significant at the 5% level. This shows that the bankruptcy risk of the major automobile maker, SAIPA, is transmitted to automobile parts companies. The coefficients α and β are also significant at the 5% level, indicating a correct estimation of the DCC model. The results of the Ljung-Box test with the null hypothesis of no correlation for the residuals and the second residual power are presented in the third part indicating that the null hypothesis of zero correlations between the residuals and the second residual power is rejected and thus the model is correct.

## 5 Conclusion and propositions

This research examines the financial distress spillover in automobile supply chain companies. For this purpose, two groups of automobile supply chain companies in Tehran Stock Exchange including Iran Khodro Companies and SAIPA Companies were selected. The reason for choosing these two groups is that they account for over 80% of the Iranian automobile market share. The KMV and VAR-DCC models have been used to investigate the bankruptcy risk of the supply chain companies. First, based on data on asset and debt value, standard deviation of return on assets, and risk-free rate of return through the KMV model, the distance to default (financial distress) of supply chain companies was estimated and then using VAR-DCC model, the financial distress among supply chain companies was examined.

The results of model estimation for Iran Khodro supply chain companies showed that the default probability (financial distress) by Iran Khodro Company (main company) spillovers on the default probability of supply chain companies (Khatoukh ،Khafner and Khosaz). Also the model estimation results for SAIPA supply chain companies showed that the default probability of SAIPA (the main company) was lower than that of Kesapa, Plasak and Khazin (automobile parts supplier companies). Therefore, the results of the research conducted at the Tehran Stock Exchange are consistent to the results of [30]stated that the performance and profitability of domestic suppliers is strongly influenced by the change in the approach of the parent firm. And major companies are trying to increase their competitiveness and profitability by importing intermediate production inputs from foreign countries during the financial crisis. Therefore, in a critical economic situation, the financial distress spillover from the parent company to the suppliers of components and raw materials will be more intensive. As we have seen, in Iran, as the US and Europe expanding their sanctions, automobile companies were dramatically influencing domestic parts companies by substituting Chinese parts for domestic products. While this has improved the profitability of the original company (due to lower production costs), it has increased the likelihood of the supply chain companies default and also financial distress. The results of this study showed that the probability of financial distress in both Iran Khodro and SAIPA companies affected their supply chain companies. These results indicated that when major companies experience crisis or financial distress (with high default probability), the financial distress is expanded to other companies and more likely they encounter with crisis or even financial distress.

However, the results of the two models showed that SAIPA default probability had a greater impact on the probability of its supply chain companies comparing to Iran Khodro. Generally, the results depicted that SAIPA had more impact on its supply chain than Iran Khodro. This may be due to the greater variety of Iran Khodro supply chain companies and the larger size of the company. Therefore, considering the results of the research on the automobile supply chain companies default probability, it is suggested that investors should not only rely on correlation analysis of return on investment and the financial distress spillover in firms. They should involve the supply chain in their decision-making.

## Appendix

VAR(1)-BEKK model estimation results for SAIPA supply chain

**a) VAR(1) model estimation results**

$$\begin{bmatrix} Kesapa_t \\ Khazin_t \\ Khsapa_t \\ Plask_t \end{bmatrix} = \begin{bmatrix} \mathbf{0.003} \\ (0.01) \\ \mathbf{0.002} \\ (0.02) \\ \mathbf{0.002} \\ (0.00) \\ \mathbf{0.006} \\ (0.02) \end{bmatrix} + \begin{bmatrix} \mathbf{-0.15} & \mathbf{0.02} & \mathbf{-0.03} & \mathbf{0.03} \\ (0.02) & (0.22) & (0.28) & (0.16) \\ \mathbf{0.31} & \mathbf{0.09} & \mathbf{-0.10} & \mathbf{0.03} \\ (0.00) & (0.04) & (0.12) & (0.48) \\ \mathbf{0.24} & \mathbf{0.11} & \mathbf{-0.20} & \mathbf{0.03} \\ (0.00) & (0.00) & (0.00) & (0.60) \\ \mathbf{0.035} & \mathbf{0.02} & \mathbf{-0.01} & \mathbf{0.02} \\ (0.70) & (0.56) & (0.06) & (0.70) \end{bmatrix} \times \begin{bmatrix} Kesapa_{t-1} \\ Khazin_{t-1} \\ Khsapa_{t-1} \\ Plask_{t-1} \end{bmatrix}$$

**b) BEKK model estimation results**

$$H_t = C^{*'}C^* + A^{*'}\varepsilon'_{t-1}\varepsilon_{t-1}A^* + G^{*'}H_{t-1}G^*$$

$$\boldsymbol{A} = \begin{bmatrix} \mathbf{0.50} & \mathbf{-0.31} & \mathbf{0.17} & \mathbf{0.37} \\ (0.00) & (0.00) & (0.00) & (0.00) \\ \mathbf{0.05} & \mathbf{0.23} & \mathbf{-0.35} & \mathbf{-0.30} \\ (0.05) & (0.00) & (0.00) & (0.00) \\ \mathbf{0.06} & \mathbf{0.41} & \mathbf{1.21} & \mathbf{0.11} \\ (0.00) & (0.00) & (0.01) & (0.92) \\ \mathbf{-0.14} & \mathbf{-0.29} & \mathbf{0.18} & \mathbf{0.18} \\ (0.00) & (0.00) & (0.09) & (0.18) \end{bmatrix} \qquad \boldsymbol{G} = \begin{bmatrix} \mathbf{0.89} & \mathbf{-0.22} & \mathbf{0.11} & \mathbf{0.15} \\ (0.00) & (0.00) & (0.304) & (0.00) \\ \mathbf{-0.29} & \mathbf{-0.73} & \mathbf{-0.16} & \mathbf{0.02} \\ (0.05) & (0.00) & (0.440) & (0.188) \\ \mathbf{0.04} & \mathbf{0.40} & \mathbf{0.36} & \mathbf{-0.42} \\ (0.00) & (0.00) & (0.01) & (0.89) \\ \mathbf{-0.12} & \mathbf{-0.45} & \mathbf{-078} & \mathbf{-0.61} \\ (0.00) & (0.00) & (0.09) & (0.00) \end{bmatrix}$$

**c) Test results**

| Plask | Khsapa | Khazin | Kesapa | Results of Ljung-Box |
|---|---|---|---|---|
| 2,63(0,62) | 4,15(0,38) | 4,28(0,36) | 3,36(0,49) | Q(4) |
| 7,70(0,10) | 1,50(0,82) | 5,09(0,27) | 9,59(0,05) | $Q^2(4)$ |

VAR(1)-BEKK model estimation results for Irankhodro supply chain

**a) VAR(1) model estimation results**

$$\begin{bmatrix} Khtogha_t \\ Khfanar_t \\ Khosaz_t \\ Khodro_t \end{bmatrix} = \begin{bmatrix} \mathbf{0.006} \\ (0.65) \\ \mathbf{0.002} \\ (0.08) \\ \mathbf{0.003} \\ (0.02) \\ \mathbf{0.004} \\ (0.72) \end{bmatrix} + \begin{bmatrix} \mathbf{-0.04} & \mathbf{0.04} & \mathbf{0.07} & \mathbf{0.09} \\ (0.45) & (0.18) & (0.09) & (0.08) \\ \mathbf{0.12} & \mathbf{-0.01} & \mathbf{0.07} & \mathbf{0.16} \\ (0.03) & (0.74) & (0.85) & (0.01) \\ \mathbf{0.08} & \mathbf{0.01} & \mathbf{0.10} & \mathbf{0.20} \\ (0.87) & (0.77) & (0.03) & (0.00) \\ \mathbf{0.13} & \mathbf{0.07} & \mathbf{0.06} & \mathbf{0.22} \\ (0.76) & (0.81) & (0.04) & (0.01) \end{bmatrix} \times \begin{bmatrix} Khtogha_{t-1} \\ Khfanar_{t-1} \\ Khosaz_{t-1} \\ Khodro_{t-1} \end{bmatrix}$$

**b) BEKK model estimation results**

$$H_t = C^{*'}C^* + A^{*'}\varepsilon'_{t-1}\varepsilon_{t-1}A^* + G^{*'}H_{t-1}G^*$$

$$\boldsymbol{A} = \begin{bmatrix} \mathbf{-0.36} & \mathbf{-0.25} & \mathbf{-0.33} & \mathbf{-0.14} \\ (0.00) & (0.00) & (0.00) & (0.00) \\ \mathbf{0.05} & \mathbf{0.42} & \mathbf{0.27} & \mathbf{0.30} \\ (0.44) & (0.00) & (0.00) & (0.00) \\ \mathbf{0.23} & \mathbf{0.21} & \mathbf{0.32} & \mathbf{0.06} \\ (0.00) & (0.00) & (0.00) & (0.19) \\ \mathbf{-0.10} & \mathbf{-0.36} & \mathbf{-0.42} & \mathbf{0.04} \\ (0.00) & (0.29) & (0.00) & (0.61) \end{bmatrix} \qquad \boldsymbol{G} = \begin{bmatrix} \mathbf{-0.59} & \mathbf{0.06} & \mathbf{0.58} & \mathbf{-0.09} \\ (0.00) & (0.07) & (0.00) & (0.00) \\ \mathbf{0.41} & \mathbf{0.01} & \mathbf{0.11} & \mathbf{-0.13} \\ (0.00) & (0.09) & (0.04) & (0.25) \\ \mathbf{-0.56} & \mathbf{0.19} & \mathbf{0.92} & \mathbf{-0.72} \\ (0.31) & (0.00) & (0.01) & (0.21) \\ \mathbf{0.27} & \mathbf{-0.05} & \mathbf{0.27} & \mathbf{1.02} \\ (0.00) & (0.26) & (0.00) & (0.00) \end{bmatrix}$$

**c) Test results**

| ***Khosaz*** | ***Khodro*** | ***Khfanar*** | ***Khtogha*** | ***Results of Ljung-Box*** |
|---|---|---|---|---|
| 4,63(0,30) | 4,15(0,38) | 3,34(0,48) | 4,28(0,36) | Q(4) |
| 2,18(0,62) | 1,83(0,75) | 5,29(0,31) | 8,52(0,06) | $Q^2(4)$ |

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