Modelling and Investigating the Differences and Similarities in the Volatility of the Stocks Return in Tehran Stock Exchange Using the Hybrid Model PANEL-GARCH

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ABSTRACT

Efficient financial markets with high degree of transparency do not substantiate the hypothesis that there are differences in the volatility of return. Generally, there are factors rejecting any perfect similarity in the volatility of return in the emerging stock markets, as previous studies in Iran have confirmed the complete difference. On the other hand, the hybrid model PANEL-GARCH has the benefit of high process accuracy, suggesting that the evaluation of the similarity in the volatility of return at the level of market or industry constituent units is better than the simple technique of time series GARCH model for the entire market (instead of evaluation at unit levels). Therefore, the present study intends to investigate complete similarities or differences in the volatility of return in Iran's industries. Results showed that the assumption of complete difference in the volatility of return in the industries did not hold. The results of this process for Iran's industries covering the timespan between 16/2/2013 to 18/3/2017 showed that there are similarities in terms of the y-intercept of conditional mean and variance equations (1.1) PANEL-GARCH between the volatility of stock returns of 23 industries in the Tehran Stock Exchange as confirmed by LRT test.

1 Introduction

The volatility of financial markets has an extremely profound effect on the macro economy of countries. The volatility higher than a certain threshold increases the investment risk and causes concern of private investors and investment institutions with respect to volatile financial markets and economies [17]. On the other hand, considering the importance of volatility, financial researchers have proposed many econometric models. This follows from the need for modelling uncertain conditions and for latent risk management. Return on financial assets generally has three important features: cluster volatility, asymmetrical relationship (advantage), and non-linearity. Owing to their compliance with these features, the conditional variance heterogeneity models are widely used in financial studies [4]. It is obvious that under conditions where there is heterogeneity of variances, the variance of the variable, which is a constant and indicates volatility, cannot very well explain the dynamic structure of volatility. The models ARCH and GARCH are specifically designed to meet these needs and modelled to predict the variance or rather to evaluate the dynamic volatility. In this respect, the models such as

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autoregressive conditional heteroscedasticity model (ARCH) and the generalized autoregressive conditional heteroscedasticity (GARCH) were developed by Engle and Bollerslev, respectively. The strength of GARCH is that it is based on strong economic and financial theory. However, changing market conditions always engender a lot of disturbing elements; therefore, the number of explanatory variables should be constantly increased to improve the model. On the other hand, the time series models are subject to restrictive assumptions as to the distribution of time series. Accordingly, in many cases, it does not seem logical to rely on the raw output of these models and the conclusion will be far from reality [19].

Using panel data analysis for financial data has many advantages over the study of time series or cross-sectional data. First, in modelling behavioural differences between specific stocks, the panel data allow more flexibility to the researchers with increased sample size. Compared to cross-sectional data and standard time series data, panel data enjoy a higher degree of freedom and sample variability. In this respect, they enhance the efficiency of econometric estimates and precision of the estimates. Second, due to the fact that dynamic panel data include information about the dynamic relationship between periodicity and uniqueness of the inputs, they help to control the effects of excluded or unobserved variables. This method allows a more accurate analysis of a specific variable by completing its observations in the problem along with other similar variables [6]. Another reason for using panel data instead of a single time series is the restrictions associated with distributions in statistical tests. With the use of panel data, rather than following non-conventional distributions, the statistical distribution remains asymptotically normalized, and is almost normally distributed for the sample sizes used in the financial markets [10]. Emerging markets suffer greater volatility compared to developed markets. Similarly, developing capital markets are different from developed markets in that the former enjoy greater efficiency and lower correlation [3]. A typical developing capital market is that in Iran. As in other developing markets, Iran has made efforts to develop her capital markets, including privatization, facilitation of foreign investment and development of financial institutions to name a few. Accordingly, Tehran Stock Exchange, as the capital market of Iran, calls for further future studies for its development. Moreover, Securities Exchange halls have expanded and the public sector companies have joined this market (in accordance with Article 44 of Iran's constitution) so much so that the evaluation of similarities and differences in the volatility of returns in different industries can confirm or reject any advance towards efficient market in the process of assigning more shares to non-institutional shareholders. The purpose of this study was to investigate the differences and similarities in the volatility of the return on equity stocks in Tehran Stock Exchange using the hybrid model PANEL-GARCH.

2 Literature Review

Panel data are the integrated observations from cross-sectional data related to households, countries, and firms, collected during different times. These data are obtained by statistical analysis and random sampling through survey of households, firms and countries carried out at regular intervals. The observations cover not only the individual but also the same individuals over time [11].

Hsiao [9] has listed many benefits to using panel data as follows:

1. Panel data control heterogeneity of the individuals. The basic idea behind the panel data is that individuals, firms and households are not homogenous in terms of behavioural pattern. The time series data and cross-sectional data models cannot alone model the inhomogeneity. As a result, in case of heterogeneity, its estimators are biased.

2. Panel data generate data with high size, considerable variability, and low collinearity among variables, higher degrees of freedom and greater efficiency. Time series models usually suffer collinearity.

3. Accuracy of the data. Panel micro data collected on individuals, firms, households can be more accurately collected, and measured compared to the same variables collected at the macro level, thus, the models based on panel micro data do not suffer aggregation bias.

4. Solution for short data intervals. One of the problems of micro data concerning the individuals, firms and households is that the size of observations is very limited in terms of time. The integration of cross-sectional and time-series data can help reduce small data size.

5. Compared with purely cross-sectional or time-series data, panel data had better address the complexities of dynamic behaviours.

The econometric of panel data is expanding. This model makes use of two aspects of data (cross-sectional and time). In a general framework, this model is defined as the following equation:

$$Y_{it} = \alpha_{it} + \beta^T_{it} x_{it} + u_{it} \tag{1}$$

Where I = 1… n is the index of cross-sections (e.g. firms), t= 1, …, T is the time index and u_{it} is the error statements that are not estimated. As for the model components, certain assumptions can be made. The most common assumption is that the parameters of the model are assumed to be homogeneous, in the sense that $\alpha_{it} = \alpha$ and $\beta_{it} = \beta$ for all ts and is. In this respect, the model is obtained as follows:

$$Y_{it} = \alpha + \beta^T x_{it} + u_{it} \tag{2}$$

In this model, all the data for indexes t and i are merged. If it is necessary to mode the heterogeneity of the sections, it is often assumed that error statements are of two components one of which is determined by the corresponding section and does not change over time. This model is known as an invisible effect model:

$$Y_{it} = \alpha + \beta^T x_{it} + \mu_i + \varepsilon_{it} \tag{3}$$

The best method for estimating this model depends on the characteristics of the two components. With respect to the error statement ε_{it}, it is generally assumed that it has good behaviour and the explanatory variables as well as the component of the cross sectional error μ_i be independent. The component μ_i may be independent or correlated, which is known by fixed and random effects. If the common assumptions about error statements, that is, the white noise with good behaviour, are excluded and the heterogeneity of self-correlation variance is allowed over time, a more unrestricted and general method, such as GLS, is recommended for estimation.

A flexible framework for calculating the coefficients of robust covariance matrix is to use the general estimator of white system as follows:

$$V(\text{B}) = (X^T X)^{-1} \sum_{i=1}^{n} X_i T E_i X_i (XTX) - 1 \tag{4}$$

Where in E_i is a function of waste e_{it} for which heterogeneity of variance and correlation structure is permitted. To determine the appropriate model, different tests are used in relation to parameters and error statements. First, it is necessary to compare the estimation using sample data and that based on the equations fitted as per section. Second, after the homogeneity test of the parameters, it is necessary to test the null hypothesis based on spherical waste. Following the above-mentioned steps of the test,

the appropriate model is selected for defining the behaviour of the variable. Simultaneous use of models GARCH / ARCH and the panel method for financial data in the literature seems to be newer than the standard time series data. Here is a brief overview of the research done in this field, which simultaneously uses panel data and GARCH.

Kitazawa [13] and Cermeno et Grier's [7] are two articles the set the main foundations of other researches in this field. Kitazawa used ARCH to estimate a panel data model with fixed effects using a great number of stocks ($N \rightarrow \infty$) in a short interval (Fixed T). In this study, they addressed the leverage effect and its impact on stock returns and a negative association between stock returns today and the volatility in stock returns in the next day. Using four specific models and a unique methodology, Cermeno et Grier's tested and estimated the effects of GARCH in panel data to determine the most appropriate model. They first, using simple tests based on wastes OLS and LSDV, began to determine the existence of GARCH effect and to examine the unique effects in the conditional variance equation. Model estimation is directly based on the maximization of the log-likelihood function using numerical methods. Similarly, in his study, Monte Carlo simulation method has been used in order to evaluate the efficiency of MLE estimator. In addition, two experimental operations were done including a panel of investment data of five large industrial firms in US and also inflation in a panel of seven Latin American countries to investigate the effect of GARCH. In both cases, the estimator GARCH, using the concept of panel, significantly showed the heterogeneity of conditional variance in the data.

In the same vein, Kling [14] carried out a field study to find out the effect of merger of small companies on their market value by observing deviation of daily returns from the normal price of stocks for 46 companies. Any significant deviation from the normal price of stocks was construed as a sign that the merger has an economic impact on the firm's market value, which includes unusual returns. Kling used a GARCH (p,q) model to test the unusual uncertainty in the unusual daily returns caused by such events. Estimation of the variance equation in his model was done assuming the sameness of all parameters for all of the cross sections. This assumption is the same as that used by Cermeno et Grier in one of their four models. This method has been frequently used in such subjects as volatility, growth, exchange rates and inflation uncertainty. For example, in an experimental article, Apergis [1] explained the relationship between inflation uncertainty and economic growth through a panel data of OECD countries and GARCH. The main results indicate that uncertainty in inflation has had a reverse effect on the economic growth of the countries under study. Babai [2] addressed the volatility of the stock return in Tehran Stock Exchange using panel data and GARCH.

Using a panel data consisting of indicators of several industry groups as samples and the time series associated with the price of shares in these industry groups in Tehran Stock Exchange, he sought to investigate the similarities and differences in the volatility of the returns of the shares within similar industries. As well as the volatility of the returns of the shares within dissimilar industries. His results showed that no similar volatility could be considered for the shares in an industry group or, at a higher level, for the sample industry groups selected from the Tehran Stock Exchange in terms of stock returns, similar volatility of the return, or similar average volatility of returns.

3 Methodology and Research Hypothesis

In the present study, we are to answer this question: what are the differences and similarities in the volatility of different industries?

- The volatility of different industries is not the same.

The model PANEL-GARCH (p,q) has two advantages. First, you do not need a long time interval so that the size sample is large enough. Thus, it is possible to shorten the time interval so that new data can be used for modelling; as a result, consideration of the recent data can increase the model capacity. Second, the sample can include a variety of companies and industries in the Stock; accordingly, the model is estimated based on the information resulting in better identification of the behaviour of financial variables [18]. Then, the model PANEL-GARCH (p,q) is as follows:

$$Tepix_{it} = m + X_{it}b + u_{it} \tag{5}$$

Where in the mean equation (5), m represents the fixed or random effects of the industries i. X is a vector of the dummy variables representing the efficiency of the industries. For a time, series, the time volatility model of the returns is defined as follows:

$$y_t = \mu_t + \varepsilon_t$$
$$\varepsilon_t|\epsilon_{t-1} \sim N(0, h_t)$$
$$h_t = \alpha_0 + \sum_{m=1}^{q} \alpha_m \varepsilon_{t-m}^2 + \sum_{n=1}^{p} \delta_n h_{t-n} + \pi_t \; ; \; \pi_t = N(0, h_\pi) \tag{6}$$

Where in equations (6):

y_t: is the dependent variable representing the industry's return index.

ε_{t-1}: data from past to t-1.

α_0: A fixed number.

h_{t-n}: Conditional variance.

$\varepsilon_t^2 - m$: News related to the volatility of return of industries (GARCH statement).

h_{t-n}: ARCH statement or the conditional variance with n periods of delay.

In a panel of series, a general model allows all parameters such as $\mu_t, \alpha_0, \alpha_m...\alpha_1, \delta_n...\delta_0$ to vary along all the series in the panel. This model is called "Model A or General Model". Using this model, various models can be obtained based on the restrictions corresponding to a combination of various parameters for specific series in each panel. This is obtained owing to the tests based on this general model and, in this way, the similarities and differences of volatility between an industry or sector with another industry or sector are tested.

First of all, one has to pay attention to problems arising from the complexity of estimating certain models with a large number of parameters:

Firstly, while all the conditional variance equations are generalized to GARCH (p, q), one has to remember that the estimated models are limited to GARCH (1, 1). The GARCHs of upper echelons entail a large number of parameters that must be estimated in the panel model. It also prevents the creation of too many sub-models.

Secondly, during the analysis, we assumed the independence of cross-sectional data. This means that the time series in a panel are independent from each other. This assumption is equivalent to the fact that the covariance between specific stocks within each panel is considered equal to zero.

This limitation significantly reduces the number of parameters that must be estimated in the equation of variance with panel structure. Now, with a diagram of all the sub-models that can be extracted from the general model, we go into the details of the general-to-specific modelling formed by imposing restrictions.

Model A: General model (variable coefficients model)
This model is defined as follows:

$$y_t = \mu_t + \varepsilon_t \quad ; \quad i = 1,2,...N \;, \; t = 1,2,...T \; ; \; \varepsilon_t|\epsilon_{t-1} \sim N(0, h_t) \tag{7}$$

According to Bollerslev's model (1986), for a single time series, the conditional variance equation in the panel is as follows:

$$h_{ti} = \alpha_{0i} + \sum_{m=1}^{q} \alpha_{mi}\varepsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_{ni}h_{i,t-n} + \pi_{it} \; ; \; \pi_{it} = N(0,h_\pi) \; i = 1,2,\dots,N \qquad (8)$$

Where, α_0 is a fixed expression and forms an independent part of the volatility time. As is obvious from its name (variable coefficients model), the main feature of this model is that all the estimated coefficients can vary. There is no restriction on the parameters and thus coefficients are not fixed.

When modelling, as a general model, it cannot be taken into account as the most efficient model to determine the process of sublayer data (data at panel unit levels for each industry group). To do so, certain restrictions are applied on the estimated coefficients. These restrictions are not simply meant to simplify the model to reduce the estimated parameters, but lead to a model that describes the data more accurately. The restrictions are tested using the appropriate tests. It is noteworthy that the assumptions, which are based on a simplification of the likelihood ratio test statistic, show the similarities and differences in the volatility of the time series associated with the industries in the industry panel. Figure 1 shows the framework for general volatility model along with all possible volatility models which can be built with GARCH (1, 1) and placement of the general model by applying specific restrictions on the parameters on mean and conditional variance equations. The application of restrictions follows the steps below:

First step: Assumption of an equal mean ($\mathbf{\mu}$)

The application of restrictions results in the model B. In this model, the relationship (7) is converted as follows:

$$y_t = \mu + \varepsilon_t \quad ; \quad i = 1,2,\dots N \; , \; t = 1,2,\dots T \; ; \; \varepsilon_t|\epsilon_{t-1} \sim N(0,h_t) \qquad (9)$$

As stated above, in case of the validity of these restrictions, we will address more restrictions by taking into account the equal mean of returns, which lead to next conditions:

Second step: Assumption of equal variance equation slope parameters (GARCH statements (that's $\boldsymbol{\alpha_m}$ and ARCH statements (that's $\boldsymbol{\delta_n}$))

With this restriction, the variance equation given in (8) is modified as follows:

$$h_t = \alpha_{0i} + \sum_{m=1}^{q} \alpha_m \varepsilon_{t-m}^2 + \sum_{n=1}^{p} \delta_n h_{t-n} + \pi_t \; ; \; \pi_t = N(0,h_\pi) \qquad (10)$$

Third step: The assumption of equal mean of returns volatility

With this restriction and in case of the invalidity of the restriction in the second step, the variance equation given in (8) is modified as follows:

$$h_{ti} = \alpha_0 + \sum_{m=1}^{q} \alpha_{mi}\varepsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_{ni}h_{i,t-n} + \pi_{it}; \; \pi_{it} = N(0,h_\pi) \; i = 1,2,\dots,N \qquad (11)$$

And if the restriction of step two is valid, the variance equation will be as follows:

$$h_{ti} = \alpha_0 + \sum_{m=1}^{q} \alpha_m \varepsilon_{i,t-m}^2 + \sum_{n=1}^{p} \delta_n h_{i,t-n} + \pi_{it} \; ; \; \pi_{it} = N(0,h_\pi) \; i = 1,2,\dots,N \qquad (12)$$

The first restriction applied is to take into account the fixed mean of returns for all sections of the cross-sectional data which form the model B in figure 1. If the null hypothesis of this restriction holds for an industry in the panel, it indicates that mean of returns for all the industries in the panel is fixed and if the null hypothesis holds for the panel of indices indicates that mean of returns for all the market is fixed. If the null hypothesis is not rejected, the restriction of the first step is maintained and the next restrictions are applied; as a result, the left wing of figure 1 is followed. However, if the null hypothesis is rejected, the variable parameters model (Model A) is maintained and the restrictions applied on conditional variance equation parameters should be tested; as a result, the right wing of figure 1 is followed. Figure 1is symmetric and the only difference between the two halves is in the fixing of

parameter μ for all panel units forming the left half of the figure and the parameters μ varies for all the time series in the panel forming the right half of the figure. The application of restrictions on variance equation is the same for each half of Figure 1.

After testing the assumption of restrictions in the first step, the restrictions associated with the parameters of the variance equation slope are tested. In this test, the null hypothesis is that the variance equation slope statements GARCH (that's α_1) and ARCH (that's δ_1) are the same for all panels; the opposite hypothesis is that the parameters α_1 and δ_1 are the units of a different panel. In other words, the test of the null hypothesis, where different institutions in the panel have different volatility mean (α_0) (because there is still no restriction on this parameter in this step) and show the same intersectional pattern on those means, is contrasted with the hypothesis where different institutions in the panel have different volatility mean and show different intersectional pattern on those means. If the null hypothesis cannot be rejected, then we have model C or model F (in case of rejection or acceptance of the hypothesis of equal μs in the restrictions test of the first step, and more restrictions will be applied on the variance equation of these models. Otherwise, if the null hypothesis can be rejected, the model accepted in the test maintains the first restriction which is one of the models A or B and more restrictions are to be applied on its variance equation. In this case, we have followed the right wing of the model accepted in the first step. With an overview of the whole figure, we can see that the left and right wings of the model accepted in the first step are symmetric, upon certain restrictions on the variance parameters.

After performing the tests of step 1 and 2, we come to the restriction test of step 3. In fact, this restriction shows that the parameter α_1 is considered fixed in the units of each panel. In other words, it indicates whether the mean volatility of Stock returns for all industries is fixed against each industry in the panel or not? To test the restrictions from the general model to the restricted models, we use LRT method. This method is used when the restricted model is replaced by a more complex model and, essentially, it tests the different performance between the estimates of the two models. At each step of comparison between the models and evaluation of validity of restrictions, the values of the test statistic will be compared with the Chi-2 distributions at a level of 5%. The lower we go down the left wings, the higher levels of generality we can see in the remaining model parameters; the lower we go down the right wings, the higher levels of difference in the parameters between units of the panels. Consequently, the two models in the lowest level of the figure 1 are model A on the right with all varying parameters in the panel units and model D on the left in which all parameters are the same for all units in the panel. Similarly, Fisher's maximum likelihood method (ML) is used to estimate the parameters.

4 Research Data and Statistical Sample

In most financial studies, the return is used instead of asset prices. Campbell and Mackinlay [20] offered two main reasons for the above replacement. Firstly, for the mass of investors, return on assets is a full summary and free scale of investment opportunities. Secondly, series of returns are handled more easily than those of price because, according to the records, they enjoy more attractive statistical properties.

Return on equity suggests increase in investor's wealth and is calculated by the following equation:

$$r_t = (\frac{P_t+D_t}{P_{t-1}}) * 100 \tag{13}$$

Where, r_t is the return of time t, p_t and p_{t-1} are the stock price index respectively at the end and beginning of the time period t, and D_t is the dividend paid for the stock during a period. Likewise, the return of the total market is calculated using total market index. In this respect, the return on investment
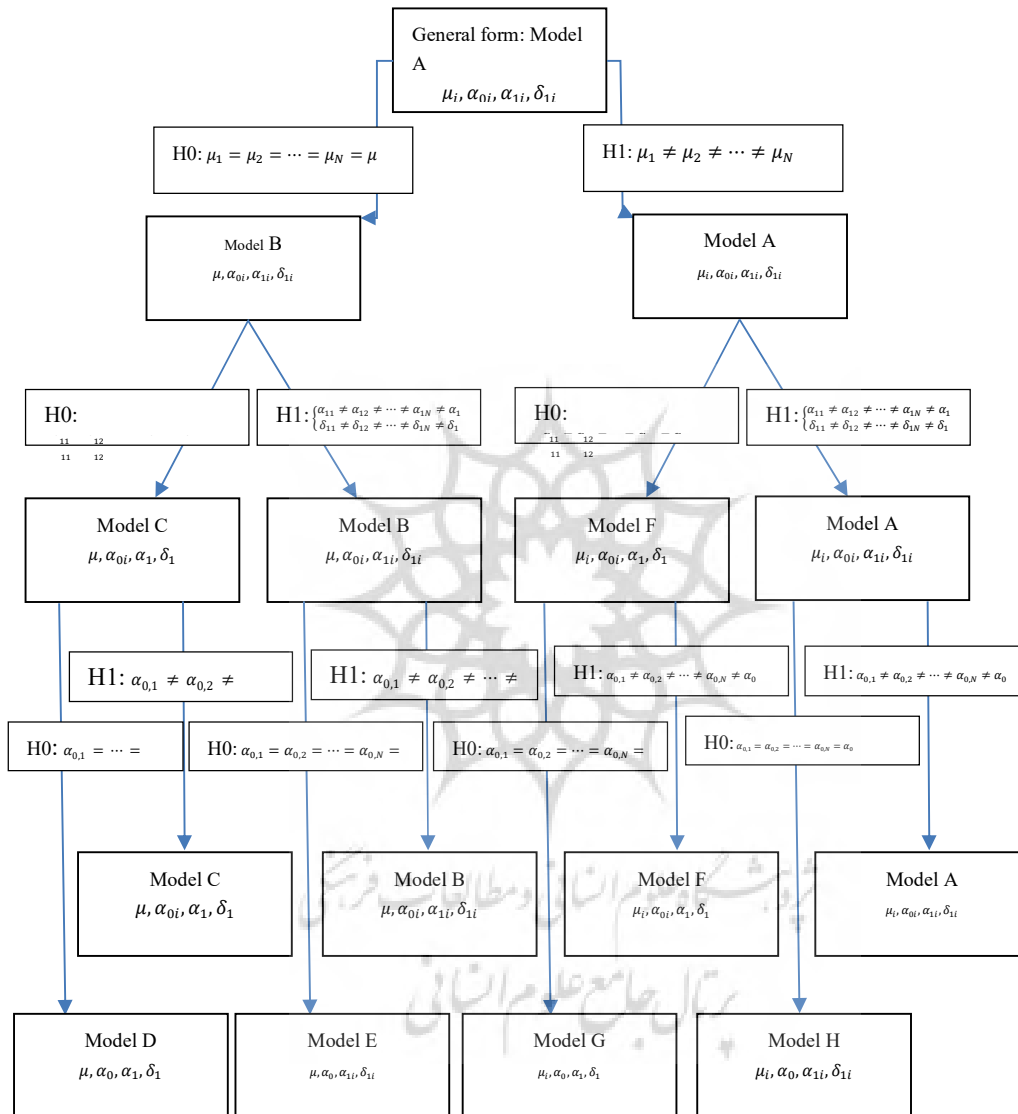
Fig. 1: General Framework for Modelling volatility: General-to-specific test of volatility models with the structure of GARCH (1, 1)

is influenced by two factors: A. the increase in stock prices, itself resulting from factors such as qualitative and quantitative changes of new investment and inflation. B. the dividend paid; in this regard, the company that pays less dividends, its funds may be spent on new investment or augmentation of liquidity, which ultimately lead to the further growth of the company's stock price. Considering that

the exclusion of stock dividends would not have a significant effect on return, the return can be obtained from the following equation [15]:

$$r_t = \left(\frac{P_t}{P_{t-1}}\right) * 100 \tag{14}$$

Similarly, Leroy and Porter [16] argue that stock returns are more volatile than the dividends reduced by a fixed rate can cover them. Generally, financial time series, especially the price of shares are non-viable, but in practice, rather than price, the return on stocks is modelled whose time-series are viable. Therefore, according to the above, the daily data price index (TEPIX) and the Industry Index (RIND) have been used in the study for modelling volatility of stock returns. For estimation of the models, the stock price index data (TEPIX) and the stock price index for each industry (RIND) were used for 23 active industries in Tehran Stock Exchange covering the time span between 16/2/2013 to 18/3/2017.

5 Results and Estimates

To evaluate the similarity in the volatility between different industries, the general-to-specific test and PANEL-GARCH modelling were used for return of the stock price index separately for each industry index. According to the principles stated in the previous section, an unrestricted model (model A) must be estimated whose results are given in Table 1:

Table 1: PANEL-GARCH model - The dependent variable RIND-Model A

Parameters	Coefficients	T statistic	p-value
μ_i	0.000467	0.8561	0.3919
Tepix	1.298637	7.127	0.0000
AR(t-1)	0.050337	0.6956	0.4867
AR(t-2)	-0.10168	-1.496	0.1346
AR(t-3)	-0.07814	-1.292	0.1962
AR(t-4)	-0.12371	-1.918	0.0551
α_{0i}	0.016275	1.222	0.2217
ARCH effect: α_1	0.041517	2.57	0.0102
GARCH effect: β_1	0.975827	163.2	0.0000

Table 2: PANEL-GARCH model - The dependent variable RIND-Selection between Model A or B

Parameters	Coefficients	T statistic	p-value
Model restriction	μ_i =0.000467		
Tepix	0.153903	1.71	0.0872
AR(t-1)	-0.04635	-0.246	0.8056
AR(t-2)	-0.03996	-0.1475	0.8827
AR(t-3)	-0.03045	-0.1128	0.9102
AR(t-4)	-0.027	-0.06758	0.9461
α_{0i}	0.179277	0.6958	0.4866
ARCH effect: α_1	0.057497	3.629	0.0003
GARCH effect: β_1	0.943078	15.17	0.0000

The results of estimation of the unrestricted model A indicate the significant effects of GARCH / ARCH in the first step. Although the convergence condition has not been met, the significant values of GARCH / ARCH (α_1 and β_1) can be used for restricted estimation of the models. Using the restrictions of the first step, the model B has been restricted by applying the restrictions that equal the fixed coefficient of mean equation with GARCH (1, 1) for all the units of the panels. In fact, this restriction suggests that the parameter μ_i is considered fixed in the panels of each unit. In other words, this restriction is valid only when the shocks or the news causing volatility in the market bear the same effect for all industries in the industry panel. What is expected is that this restriction remains valid on the industry index panel (RIND) in a competitive and fully efficient market. The results of estimation of the restricted model B are given in Table 2. What is clear is that to choose between acceptance and rejection of the above restriction, we must refer to the LRT test results indicating the goodness of fit and hence the result of acceptance or rejection of the null hypothesis indicating the significance of the restriction applied by the statistic LR of this test. The results of Table 2 show that the null hypothesis is confirmed, which suggests that model B is superior to model A.

Using the restrictions of the second step, the model C has been restricted by applying the restrictions that equal the coefficients of variance equation with GARCH (1, 1) for all the units of the panels. In fact, this restriction suggests that the parameter $_{(i)1}$ and $\beta_{(i)1}$ are considered fixed in the panels of each unit. In other words, this restriction is valid only when the shocks or the news causing volatility in the market bear the same effect for all industries in the industry panel. What is expected is that this restriction remains valid on the industry index panel (RIND) in a competitive and fully efficient market.

Table 3: PANEL-GARCH model - The dependent variable RIND-Selection between Model B or C

Parameters	Coefficients	T statistic	p-value
Model restriction	$\mu_i = 0.000467$ $\alpha_{(i)} = 0.041517$ $\beta_{(i)} = 0.975827$		
Tepix	0.153903	1.71	0.0872
AR(t-1)	-0.04635	-0.246	0.8056
AR(t-2)	-0.03996	-0.1475	0.8827
AR(t-3)	-0.03045	-0.1128	0.9102
AR(t-4)	-0.027	-0.06758	0.9461
α_{0i}	0.179277	0.6958	0.4866

The results of estimation of the restricted model C are given in Table 3. What is clear is that to choose between acceptance and rejection of the above restriction, we must refer to the LRT test results indicating the goodness of fit and hence the result of acceptance or rejection of the null hypothesis indicating the significance of the restriction applied by the statistic LR of this test. The results of Table 3 show that the null hypothesis is not confirmed, which suggests that model C is not superior to model B. Using the restrictions of the second step, the model E has been restricted by applying the restrictions that equal the fixed coefficients of variance equation with GARCH (1, 1) for all the units of the panels. In fact, this restriction suggests that the parameter α_{0i} is considered fixed in the panels of each unit. The results of estimation of the restricted model E are given in Table 4. What is clear is that to choose between acceptance and rejection of the above restriction, we must refer to the LRT test

results indicating the goodness of fit and hence the result of acceptance or rejection of the null hypothesis indicating the significance of the restriction applied by the statistic LR of this test. The results of Table 3 show that the null hypothesis is confirmed, which suggests that model E is superior to model B. The results of the general-to-specific test for identification of volatility in different industries are given in Table 5. What can be inferred from the results is that the restriction of fixed coefficient equation is confirmed according to LRT statistic. In this regard, the model proposed in in this section is shifted to the left wing of Figure 1.

Table 4: PANEL-GARCH model - The dependent variable RIND-Selection between Model B or E

Parameters	Coefficients	T statistic	p-value
Model restriction	μ_i =0.000467 $\alpha_{0i} = 0.179277$		
Tepix	0.153903	1.71	0.0872
AR(t-1)	-0.046348	-0.246	0.8056
AR(t-2)	-0.039957	-0.1475	0.8827
AR(t-3)	-0.030451	-0.1128	0.9102
AR(t-4)	-0.026996	-0.06758	0.9461
ARCH effect: α_1	0.057497	3.629	0.0003
GARCH effect: β_1	0.943078	15.17	0.0000

Table 5: General-to-specific test for identification of similar volatility in different industries

General-to-specific test for identification of similar volatility in different industries			LRT statistic	Likelihood ratio test
Null hypothesis	Opposite hypothesis	Test steps		
μ_i =0.000467	μ_i ≠0.000467	Selection between A and B	0.243579	0.6216
$\alpha_{(i)} = 0.041517$ $\beta_{(i)} = 0.975827$	$\alpha1_{(i)} \neq 0.041517$ $\beta1_{(i)} \neq 0.975827$	Selection between B and C	227.886	0.0000
$\alpha_{0i} = 0.179277$	$\alpha_{0i} \neq 0.179277$	Selection between B and E	0.484095	0.4866

However, the restriction of fixed slope of conditional variance equation (coefficients of GARCH / ARCH effects) presented in the restricted model C was not accepted according to the LRT test, because the LRT likelihood statistic was less than 0.05 and the goodness of fit was not confirmed. Moreover, for the final selection of volatility, the restriction of equal y-intercept of conditional variance equation was evaluated in model E, and the result of the LRT test showed that the accuracy of the above-mentioned restriction has been confirmed in the model E. Accordingly, the model E is confirmed by equal y-intercept of mean and conditional variance models in the return volatility of industries, and it cannot be said the return volatility of the total stock price index is completely different between the industries.

6   Conclusion

The purpose of this study was to study and analyse the similarities and differences in the volatility of stock returns between various industry groups by explaining the role of volatility of the entire market using the TEPIX index in the industry groups selected as samples. In order to achieve this goal, certain tests were performed beginning from a general model (model A) followed by application of restrictions on this model and obtaining more detailed models as well as validation of the applied restrictions. What was obtained from the results of validity tests was that the best model for explaining the constraints (according to the LRT tests given in Table 3) is the model E. Accordingly, the research hypothesis stated that the volatility of industries is not the same. Since model E is confirmed by the equal y-intercept in mean and conditional variance models in the return volatility of industries, it cannot be said that the volatility of stock returns behaves differently from industry to industry. Therefore, this hypothesis is rejected. If this hypothesis is accepted, one can say that in a competitive or efficient market, the ideal model, in which the volatility of the conditional variance equation has a complete similarity in terms of ARCH / GARCH effects among industries, is the model C or D. However, the fact that the volatility is not completely different among the industries also shows that the reasons, offered by Keshavarz Haddad and Babaei [12] for the data before those of the timespan covered in this research, suggest the adjustment of the causes of inefficiency and market competitiveness Tehran Stock Exchange. They offered the following reasons:
1. Limited increase and decrease of the daily price of stocks in the studied period.
2. Asymmetrical governmental support of certain groups of industries.
3. The stock market of Iran is a developing market and some of the shares have just entered the market.
4. Different firm risks.
5. Different firm sizes.
6. Asymmetric data in Tehran Stock Exchange.
7. Political influences and frequent changes in the structure of Tehran Stock Exchange.
One of the less addressed aspects of domestic studies is the investigation of similar volatility of stock market. The use of return on total stock price index as per industry units in a PANEL-GARCH (1, 1) model helped this investigation. By analysing it, Keshavarz Haddad and Babaei [12] showed that the volatility of stock returns is different among the industries. However, covering a different period, the present study showed that there are similarities in relation to y-intercept of the mean and the conditional variance equations of the model. An important consequence of the rejection of the research hypothesis is to contemplate the reasons that Keshavarz Haddad and Babaei had stated about the causes of the complete difference in the volatility of industries. Their first reason was the limited increase and decrease of the daily price of stocks in the studied period. On the contrary, over the period covered by the present study, the stock exchange has reduced the limit of allowed range of price fluctuation. Therefore, it is not unpredictable to incline the volatility to a similar one as a result of increasing market efficiency. Another reason for this increased efficiency is the sensitivity of reaction to market news. Growth of stock market shares is among the other reasons (third reason) offered for explaining the complete difference in the volatility of return. It should be noted that stock exchanges halls have expanded and the public sector companies have joined this market so much so that the results of this study confirm the advance towards efficient market in the process of assigning more shares to non-institutional shareholder's non-institutional shareholders, which contributed to the emergence of similarity in the industries' volatility.

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