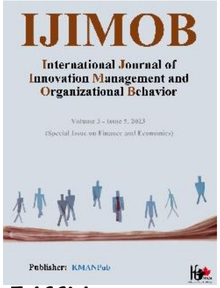
KMAN PUBLISHING INSTITUTE
Journal Website

Article history:
Received 01 September 2023
Accepted 14 December 2023
Published online 20 December 2023

International Journal of Innovation Management and Organizational Behavior

Volume 3, Issue 5 (Special Issue on Finance and Economics), pp 181-186



E-ISSN: 3041-8992

A Model for Estimating Stock Market Shocks Using the ARMA-GARCH Approach

Ebrahim. Rahimi[1*], Ahmad. Mohammadi[2], Ali Asghar. Motaghi[2], Seyyed Ali. Paytakhti Oskooe[2]

[1] PhD Student, Department of Financial Engineering, Tabriz Branch, Islamic Azad University, Tabriz, Iran
[2] Assistant Professor of Accounting Department, Tabriz Branch, Islamic Azad University, Tabriz, Iran

*** Corresponding author email address**: iacp_a-mohammadi@yahoo.com

A r t i c l e I n f o

Article type:
Original Research

How to cite this article:
Rahimi, E., Mohammadi, A., Motaghi, A. A., & Paytakhti Oskooe, S. A. (2023). A Model for Estimating Stock Market Shocks Using the ARMA-GARCH Approach. *International Journal of Innovation Management and Organizational Behavior, 3*(5), 181-186.
https://doi.org/10.61838/kman.ijimob.3.5.22

A B S T R A C T

Objective: Linear ARMA and GARCH models have numerous applications in the field of time series forecasting. The primary objective of this article is to present a model for estimating stock market shocks based on the ARMA-GARCH model in the Tehran Stock Exchange.

Methodology: For this purpose, 15-minute intraday data of the overall index and the equal-weighted index for the period from June 10, 2018, to March 18, 2019, including the opening, closing, highest, and lowest values of the mentioned indices, were used. For the analysis and fitting of the models to estimate market shocks, the Pandas, Numpy, and armagarch packages in Python 3.9 software were employed. The goodness-of-fit test was used to evaluate the suitability of the fitted models.

Findings: The results indicated that the fitted models for estimating market shocks, based on the Akaike criterion and the goodness-of-fit test, were the best and most suitable models, although the selected models differed for the two indices.

Conclusion: The findings of this study indicate that the ARMA-GARCH model is effective in estimating stock market shocks in the Tehran Stock Exchange. The optimal models identified were ARMA(2,3)-GARCH(1,1) for the overall index and ARMA(1,2)-GARCH(1,1) for the equal-weighted index. The results suggest that while the ARMA order varied between the indices, the GARCH order remained consistent, highlighting the model's robustness. Additionally, the analysis demonstrated that the new series of changes (market shocks) were completely random and non-normal, confirming the model's capability in accurately capturing market dynamics and providing valuable insights for traders and policymakers.

Keywords: *Time series, Market shock, ARMA model, GARCH model.*

1 Introduction

Nowadays, discovering appropriate patterns for predicting unexpected market shocks is a challenging issue among econometric researchers. Market shock is defined as sudden changes in the prices of financial assets. Explaining financial shocks through traditional financial models faces difficulties since conventional financial pricing models like CAPM or the Fama-French three-factor model estimate the expected market return by linearly combining historical information and adding other variables to the model's error term (Fama & French, 1993).

For market participants, finding approaches to improve the performance of future market shock predictions, although it seems simple, is a valuable effort. Successfully estimating price shocks through the development of new pricing models has benefits such as introducing trading strategies, discovering market inefficiencies, and identifying warning signs to prevent stock market crashes, which seem useful in policymaking and regulatory frameworks within the financial system (Sun et al., 2019).

According to Fuller (1998), price shock originates from three potential sources: the existence of upstream (private) information, differences in information processing capabilities, and behavioral biases. He believes that factor models or time series models have the ability to predict stock market shocks. In factor models like the Capital Asset Pricing Model and the Fama-French three-factor model, price shock is considered a price anomaly (or alpha) (Xiao et al., 2017; Zhang et al., 2016).

Previous research has examined the impact of heterogeneous factors on financial market shocks, including the effect of seasonal stock returns (Keim, 1983), holiday effects (Kim & Park, 1994), weather effects (Hirshleifer & Shumway, 2003), social sentiment (Da et al., 2011; Leung et al., 2016; Xiao et al., 2017; Zhang et al., 2015), opinion sharing in social networks (Park et al., 2013), and information volume (Leung et al., 2016; Park et al., 2013).

Time series prediction models focus on inferring from the linear characteristics of the data. For instance, simultaneously considering the effects of historical price returns and the error component in the past in the autoregressive moving average model, known as the ARMA model, combines the autoregressive structure of financial returns with the mean of moving errors linearly (Sun et al., 2019).

To discover optimal volatility patterns for improved prediction performance, Engle and Ng (1993) modeled the volatility component of ARMA models with the autoregressive conditional heteroskedasticity (ARCH) model (Engle & Ng, 1993). Additionally, the generalized autoregressive conditional heteroskedasticity (GARCH) model, introduced by Bollerslev (1986), is widely used in financial time series forecasting and pricing issues. Fabozzi and Xie (2017; 2019) used autoregressive models in asset pricing prediction to discover price bubbles, utilizing traditional time series models and daily data with slight volatility. In contrast, data-driven financial models like neural networks are characterized by high stock return volatility (Fabozzi & Xiao, 2017, 2019), index price volatility (Engle, 2002), and duration analysis (Engle & Russell, 1998).

Existing empirical and theoretical evidence suggests that using non-similar models with significant differences to form a combined model and obtain lower variance and error is more appropriate. Furthermore, due to the presence of variable and unstable patterns in the data, using a combined model can reduce model uncertainty, which typically arises in statistical inference and time series prediction (Abbasinejad & Gudarzi Farahani, 2014). Moreover, fitting the data initially with the ARMA-GARCH model can reduce the likelihood of overfitting, a common issue in neural network prediction.

Therefore, the overall objective of this research is to present a model for estimating stock market shocks in the Tehran Stock Exchange.

2 Methods and Materials

Given that this research involves applying nonlinear ARCH/GARCH family models in a specific context (stock market shock estimation), it is considered applied research based on its objective. Moreover, since it aims to examine the trend changes of a specific variable (market indices) over time, it is a descriptive-survey study by nature.

2.1 Data Collection Method

As the primary goal of this research is to provide a model for estimating shocks in Tehran Stock Exchange companies, theoretical resources were collected through library research, and the necessary data for research questions were collected through field research. The required data were extracted by visiting the website of the Tehran Stock Exchange Technology Management Company and using the Rahavard Novin software.

IJIMOB
E-ISSN: 3041-8992

The dataset used in this research includes two indices, the overall index and the equal-weighted index, in the Tehran Stock Exchange for the period from June 10, 2018, to March 18, 2019, including the opening, closing, highest, and lowest values for 15-minute intraday data from 9:00 AM to 12:30 PM. The data was collected from the Rahavard Novin software and the website of the Tehran Stock Exchange Technology Management Company (http://tsemc.com).

To organize the data and perform preliminary calculations on raw data, Excel software was used. For data analysis and model fitting to determine market shocks, Python 3.9 software was employed.

2.2 Data Analysis Techniques

The data used in this research for modeling and estimating stock market shocks during the period from June 10, 2018, to March 18, 2019, based on intraday data from the overall index and the equal-weighted index, collected from the Rahavard Novin software, were used. Logarithmic returns were used to calculate the returns of these indices. Using Eviews software and the augmented Dickey-Fuller or Phillips-Perron method, the stationarity of the time series returns was examined.

Regarding skewness, if the skewness of the distribution is zero, the distribution is normal; if it is greater than zero, it indicates more weight in the left tail, and if it is less than zero, it indicates more weight in the right tail. Kurtosis is equal to the normalized fourth moment; in other words, kurtosis measures the sharpness of the curve at the maximum point. The kurtosis value for a normal distribution is 3 (Johnson et al., 2001).

In the next step, market shock is estimated using the ARMA-GARCH model (a series of new changes).

2.3 Definition of Variables

2.3.1 Autoregressive Moving Average Model

In statistics and signal processing, the autoregressive moving average model, known as the ARMA model, and sometimes referred to as the Box-Jenkins model, is typically used for analyzing time series data. For time series data denoted as X_t, the ARMA model is a tool for studying and potentially predicting future values of such series. This model includes two components: autoregressive (AR) and moving average (MA). Therefore, the ARMA model is represented in the scientific literature as ARMA(p, q), where p and q are the orders of the AR and MA models, respectively. A general ARMA(p, q) model is expressed as:

$$y_t = \mu + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \ldots + \varphi_p y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta_q \varepsilon_{t-q}$$

2.3.2 Autoregressive Integrated Moving Average Model

In statistics and econometrics, especially in time series analysis, an integrated autoregressive moving average (ARIMA) model is a broader version of the ARMA model. These models are used in time series analysis to understand better or predict future trends. These models are applied when the data are non-stationary. If a time series becomes stationary after d orders of differencing and is then modeled using an ARMA(p, q) process, the original time series is an ARIMA(p, d, q) model. This model is often represented as ARIMA(p, d, q), where p, d, and q are non-negative real numbers indicating the order of autoregression, integration, and moving average, respectively. ARIMA models form a crucial part of the Box-Jenkins methodology for time series modeling (Box et al., 1970).

2.3.3 Autoregressive Conditional Heteroskedasticity Model

The autoregressive conditional heteroskedasticity (ARCH) model was proposed by Engle in 1982. This model considers the weights in variance calculation as unknown parameters and estimates them, allowing the best weights to be estimated based on the data for predicting variance. In this model, the variance of each period is explained based on the P periods of previous residuals:

$$\sigma_t^2 = \omega + \Sigma_{i=1}^{p} \alpha \varepsilon_{t-1}^2$$

This ARCH model is based on the residuals of the P previous periods and is thus denoted as ARCH(P).

2.3.4 Generalized Autoregressive Conditional Heteroskedasticity Model

This model was generalized by Bollerslev in 1986, named the generalized autoregressive conditional heteroskedasticity (GARCH) model. This model also includes the weighted average of the previous periods' squared residuals, but the weights continuously decrease and never become zero. Additionally, the setup cost of this model is low, and parameter estimation is relatively simple while being significantly successful in predicting conditional variances. The generalized model is formulated as:

IJIMOB E-ISSN: 3041-8992

$\sigma_t^2 = \omega + \Sigma_{(i=1)}^p \alpha \varepsilon_{(t-1)}^2 + \Sigma_{(l=1)}^q \beta \sigma_{(t-i)}^2$

In this model, the variance prediction for the upcoming period uses the residual series for the p previous periods and the q periods of past estimated variances and is denoted as GARCH(p, q). In other words, p is the order of the ARCH term, and q is the order of the GARCH term.

The ARMA-GARCH model is an integration of the ARMA and GARCH models. In this model, the conditional mean of the observations follows the ARMA model, and the conditional variance of the observations, given the previous observations, follows the GARCH model.

To estimate market shocks, the ARMA-GARCH model is fitted:

Given the market returns at time t, the combined ARMA(p, q)-GARCH(m, n) model is as follows:

$r_t = c + \Sigma_{(i=1)}^p \rho_i r_{(i-1)} + \varepsilon_t + \Sigma_{(j=1)}^q \theta_i \varepsilon_{(t-j)}$ (i)

$\varepsilon_t = \sigma_t z_t, z_t \sim N(0,1)$ (ii)

$\sigma_t^2 = \omega + \Sigma_{(k=1)}^m \alpha_k \varepsilon_{(t-k)}^2 + \Sigma_{(l=1)}^s \theta_l \sigma_{(t-l)}^2$ (iii)

Equation (i) determines the ARMA components, and equations (ii) and (iii) determine the GARCH components.

r_{t-i}: Autoregressive terms including historical market returns

ε_{t-j}: Moving average terms

$\alpha_k, \beta_l, \theta_j, \varphi_i$: Model coefficients

w and c: Constant coefficients

ε_t: Error term at time t (white noise process)

z_t: Standardized error term at time t

The lags p, q, s, and m are determined by fitting the best predictive model.

2.3.5 Market Shock

Shock, in general, is defined as sudden changes in the prices of financial assets. Operationally, the market shock z_t at time t is defined as:

$z_t = \varepsilon_t / \sigma_t$

The direction of the market shock at time t is determined by the sign of z_t.

2.4 Population and Sampling Method

The population includes all real or hypothetical members to whom the research results apply, as it is impossible to research all population members. Furthermore, if the sampling results are to be satisfactory, one must fully understand the set of activities and stages used to select a representative sample of the population. The first step in conducting research is to determine the research objectives, and to understand and clarify these objectives, one must first define the population from which the sample is to be selected.

The statistical sample consists of individuals selected from the population, whose information is collected and analyzed, and ultimately generalized to the population. The statistical population of the research includes the overall index and the equal-weighted index, with the period from June 10, 2018, to March 18, 2019, for 15-minute intraday data (including 2,521 data points) selected as the statistical sample.

3 Findings and Results

Initially, the intraday returns of the two indices, the overall index and the equal-weighted index, must be examined using descriptive statistics to determine the trends of variables in terms of central tendency and dispersion. Table 1 presents the descriptive statistics of the research variables. The descriptive statistics include central indices (mean, median), dispersion indices (maximum, minimum, standard deviation, skewness coefficient, and kurtosis coefficient).

Table 1

Descriptive Statistics of Intraday Returns Data

Index Type	Mean	Median	Maximum	Minimum	Standard Deviation	Kurtosis Coefficient	Skewness Coefficient
Overall Index	0.0001	-0.000023	0.0143	-0.015	0.0013	38.81	2.061
Equal-weighted Index	0.00011	0.000010	0.0105	-0.0093	0.00088	43.80	1.37

As shown in Table 1, the mean of the overall index and the equal-weighted index are very close to each other. Additionally, the skewness and kurtosis coefficients in these indices indicate that the distribution of variables is not normal.

IJIMOB E-ISSN: 3041-8992

To examine the stationarity of the intraday logarithmic returns, the unit root test is used. For this test, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were employed. The results are presented in Table 2.

Table 2

Unit Root Test Results of the Indices

Index	ADF Statistic	PP Statistic
Overall Index	-6.917 (p-value = 0.000)	-43.557 (p-value = 0.000)
Equal-weighted Index	-5.107 (p-value = 0.000)	-47.207 (p-value = 0.000)

According to the presented results, based on the ADF and PP tests, the test statistic is greater than the critical value at the 1%, 5%, and 10% probability levels, and since prob < 0.05, the time series of returns for all three indices do not have a unit root and are stationary.

Initially, to determine the ARMA order range, the optimal ARIMA model with the lowest Akaike value for the overall index and the equal-weighted index is determined: First, the ARIMA model order results and then the model outputs for the overall index are calculated, and the results are shown in figures below:

Figure 1

ARIMA(4,0,3) Model Results for the Overall Index

Dep. Variable:	r	No. Observations:	2521
Model:	ARMA(4, 3)	Log Likelihood	13218.411
Method:	mle	S.D. of innovations	0.001
Date:	Fri, 11 Feb 2022	AIC	-26420.822
Time:	12:45:09	BIC	-26374.163
Sample:	0	HQIC	-26403.890

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1.r	-0.0919	0.035	-2.591	0.010	-0.161	-0.022
ar.L2.r	0.2602	0.022	11.566	0.000	0.216	0.304
ar.L3.r	0.9258	0.013	73.254	0.000	0.901	0.951
ar.L4.r	-0.1811	0.025	-7.314	0.000	-0.230	-0.133
ma.L1.r	0.3159	0.028	11.267	0.000	0.261	0.371
ma.L2.r	-0.1708	0.034	-4.961	0.000	-0.238	-0.103
ma.L3.r	-0.9234	0.028	-33.374	0.000	-0.978	-0.869

Roots

	Real	Imaginary	Modulus	Frequency
AR.1	-0.6247	-0.7823j	1.0011	-0.3572
AR.2	-0.6247	+0.7823j	1.0011	0.3572
AR.3	1.0341	-0.0000j	1.0341	-0.0000
AR.4	5.3284	-0.0000j	5.3284	-0.0000
MA.1	-0.6292	-0.7829j	1.0044	-0.3577
MA.2	-0.6292	+0.7829j	1.0044	0.3577
MA.3	1.0735	-0.0000j	1.0735	-0.0000

IJIMOB
E-ISSN: 3041-8992

Figure 2

ARIMA(4,0,3) Output for the Overall Index

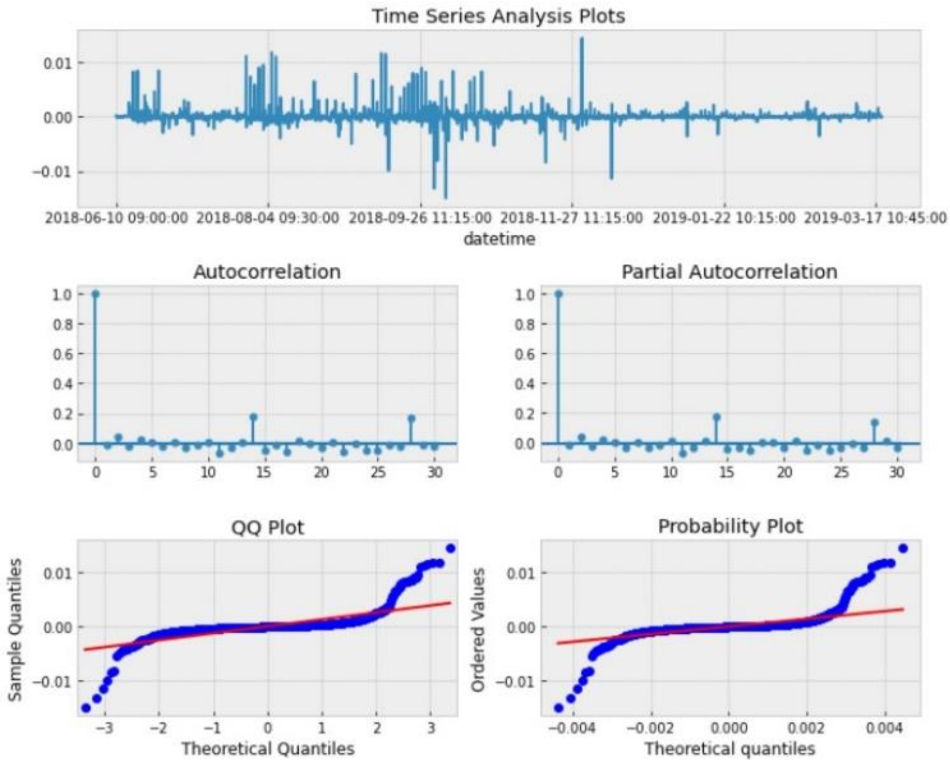
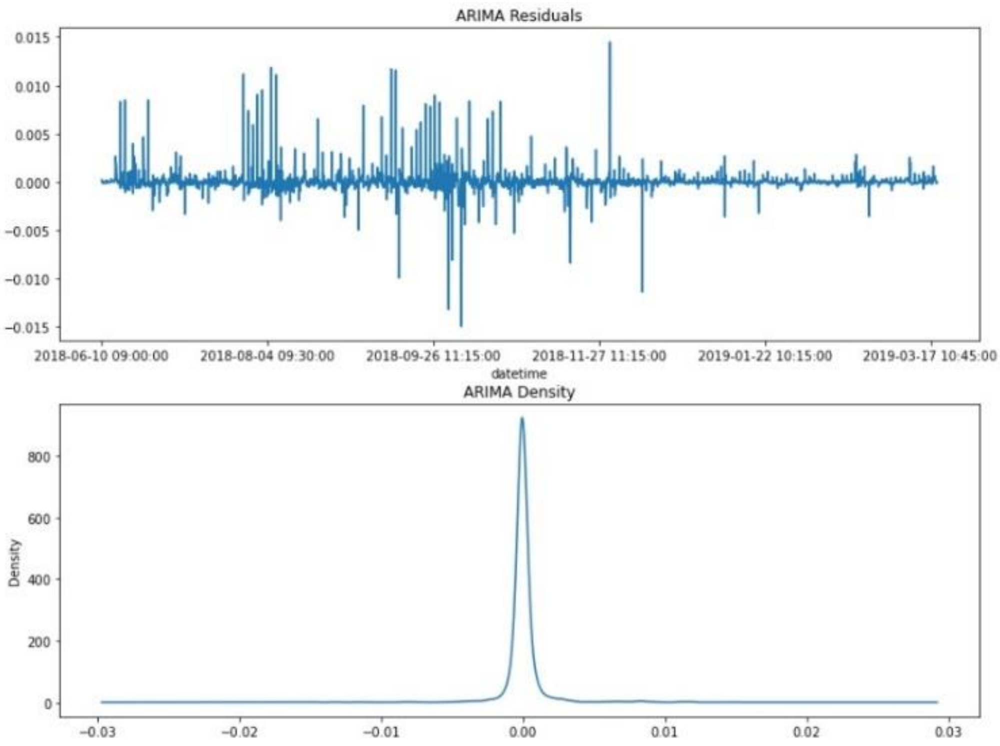


Figure 3

ARIMA Residual Output for the Overall Index



Then, for the equal-weighted index, similar to the overall index, the ARIMA model order results and then the model outputs are calculated, and the results are shown in figures below:

Figure 4

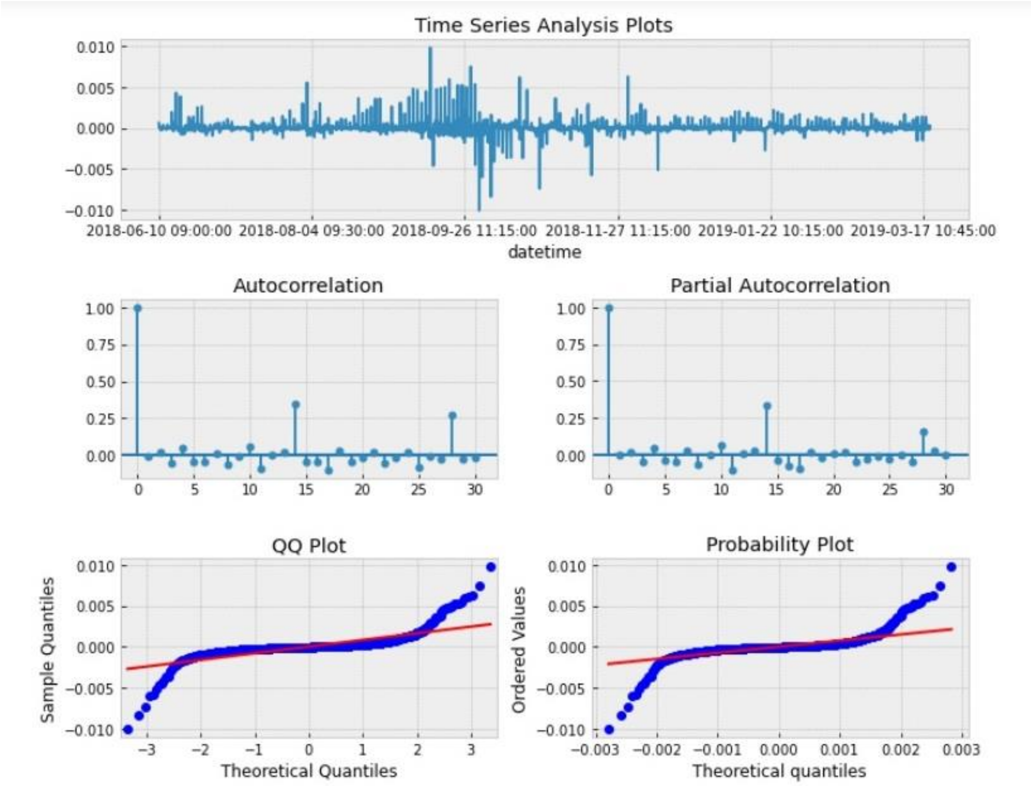
ARIMA(4,0,3) Model Results for the Equal-weighted Index

```
Dep. Variable:                     r   No. Observations:                 2521
Model:                    ARMA(4, 3)   Log Likelihood               14357.965
Method:                          mle   S.D. of innovations              0.001
Date:               Sun, 02 Jan 2022   AIC                         -28699.930
Time:                       07:41:33   BIC                         -28653.271
Sample:                            0   HQIC                        -28682.998

==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1.r       -0.0225      0.024     -0.926      0.354      -0.070       0.025
ar.L2.r        0.2638      0.011     25.064      0.000       0.243       0.284
ar.L3.r        0.9267      0.008    116.501      0.000       0.911       0.942
ar.L4.r       -0.2023      0.022     -9.398      0.000      -0.244      -0.160
ma.L1.r        0.2398      0.014     16.849      0.000       0.212       0.268
ma.L2.r       -0.1516      0.016     -9.490      0.000      -0.183      -0.120
ma.L3.r       -0.9179      0.012    -75.217      0.000      -0.942      -0.894
                                    Roots
=============================================================================
                  Real          Imaginary           Modulus         Frequency
-----------------------------------------------------------------------------
AR.1           -0.6179           -0.7959j            1.0076           -0.3551
AR.2           -0.6179           +0.7959j            1.0076            0.3551
AR.3            1.0137           -0.0000j            1.0137           -0.0000
AR.4            4.8041           -0.0000j            4.8041           -0.0000
MA.1           -0.6111           -0.8107j            1.0152           -0.3528
MA.2           -0.6111           +0.8107j            1.0152            0.3528
MA.3            1.0570           -0.0000j            1.0570           -0.0000
-----------------------------------------------------------------------------
```

Figure 5

ARIMA(4,0,3) Output for the Equal-weighted Index



IJIMOB E-ISSN: 3041-8992

Figure 6

ARIMA Residual Output for the Equal-weighted Index

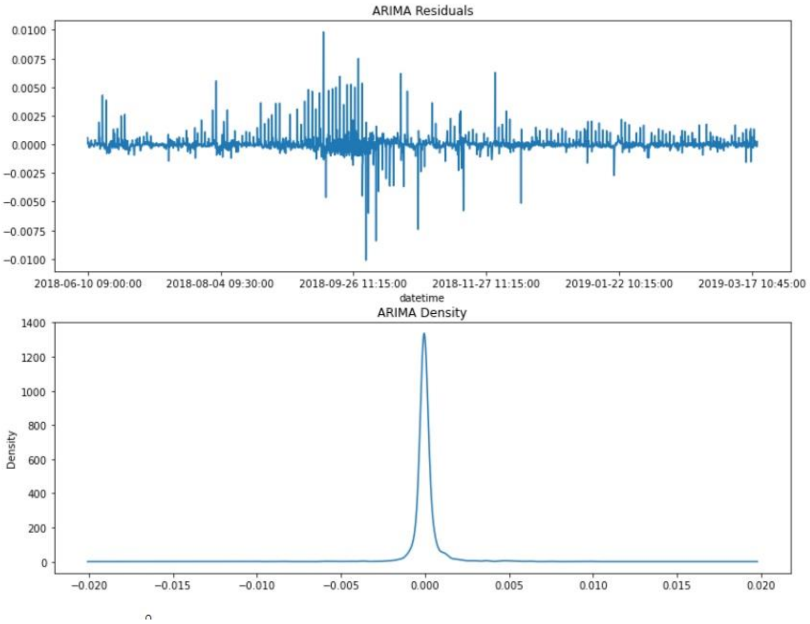


Table 3

Descriptive Statistics of ARIMA Residual Data

Index Type	Mean	Median	Maximum	Minimum	Standard Deviation
Overall Index	0.000042	-0.000043	0.014483	-0.014988	0.001278
Equal-weighted Index	0.000023	-0.000038	0.009817	-0.010115	0.000813

Given the ARIMA Density output for both the overall index and the equal-weighted index, it is observed that the distribution of the series in both indices is completely normal. Additionally, the probability values for AC and PAC for both indices are greater than 0.05, so it can be said that the new series of changes (stock market shocks) for both indices are non-random and normal. Therefore, the ARMA-GARCH combined model using the ARMA-GARCH package in Python 3.9 software will be used.

For selecting the ARMA-GARCH combined model order, different ARMA-GARCH models with various orders were tested, and in this research, Akaike criteria were used to select the appropriate model. The model with the lowest Akaike criteria value is the most suitable model. The results are shown below:

Table 4

Akaike Criteria Value and Model Order in Various ARMA-GARCH Patterns

Index	AIC	AR	MA	P	q
Overall Index	-23573.32613	2	3	1	1
Equal-weighted Index	-26368.26423	1	2	1	1

Table 5

Best ARMA-GARCH Combined Model

Index	ARMA-GARCH Model	Degrees of Freedom
Overall Index	ARMA(2,3)-GARCH(1,1)	8
Equal-weighted Index	ARMA(1,2)-GARCH(1,1)	6

IJIMOB
E-ISSN: 3041-8992

The output of the ARMA-GARCH model includes expected return, conditional variance, and standardized residuals (market shocks) for both the overall index and the equal-weighted index, as shown in figures below.

Figure 7

ARMA(2,3)-GARCH(1,1) Model Output for the Overall Index

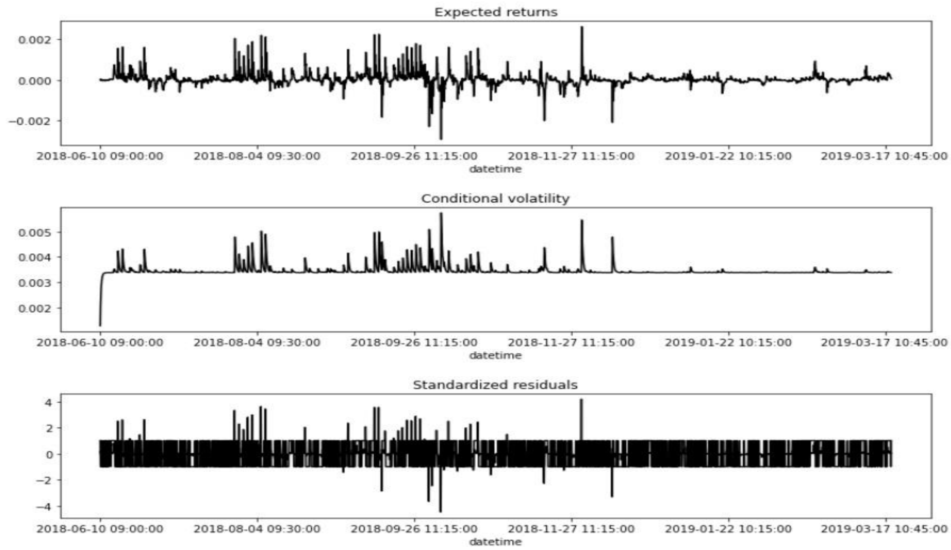
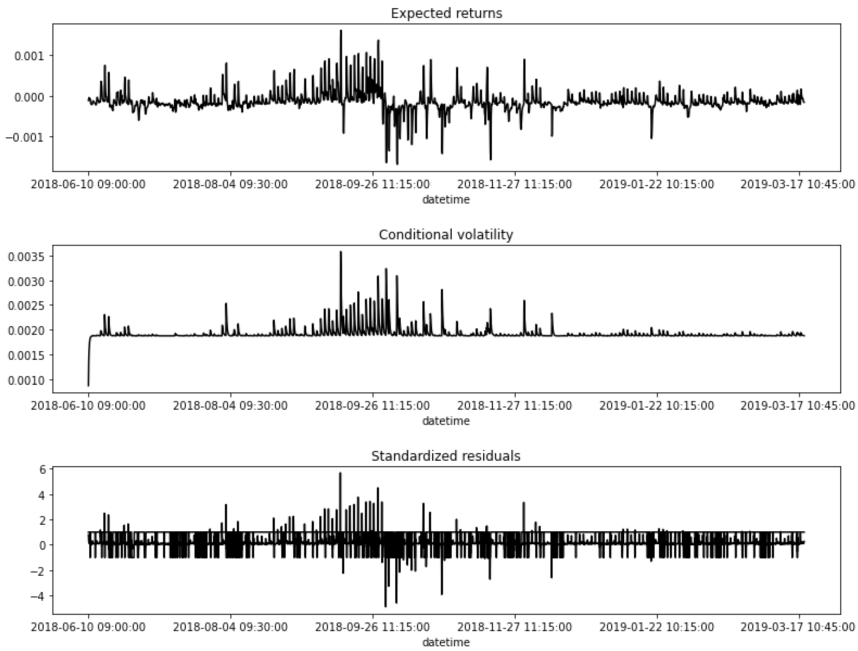


Figure 8

ARMA(1,2)-GARCH(1,1) Model Output for the Equal-weighted Index



For the goodness-of-fit test, the AC and PAC coefficients for the new series of changes are used. The AC and PAC coefficients for the new series of changes for the overall index and the equal-weighted index can be observed in figures below. As seen, the probability values for AC and PAC are less than 0.05 and are within the confidence interval. Therefore, these series observations are independent of each other, and the new series of changes are completely random. As a result, the fitted models are suitable models.

IJIMOB
E-ISSN: 3041-8992

Figure 9

AC and PAC Coefficients for the New Series of Changes in the Overall Index

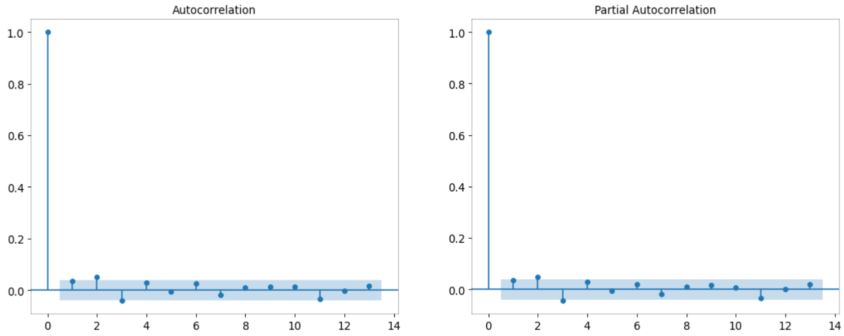
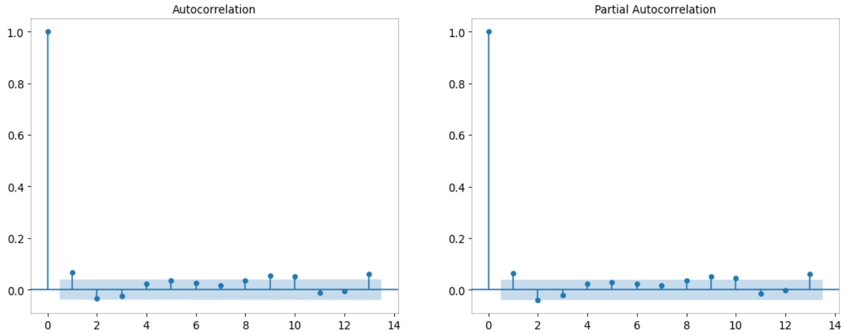


Figure 10

AC and PAC Coefficients for the New Series of Changes in the Equal-weighted Index



Given the determination of the ARMA-GARCH model orders, the optimal ARMA-GARCH model for the overall index and the equal-weighted index is determined as follows:

Optimal ARMA-GARCH Model for the Overall Index:

ARMA(2,3)-GARCH(1,1):

$r_t = 0.77 r_{t-1} + 0.514 r_{t-2} + \varepsilon_t + 0.104 \varepsilon_{t-1} - 0.48 \varepsilon_{t-2} + 0.001 \varepsilon_{t-3}$

$\sigma_t^2 = 0.09 \varepsilon_{t-1}^2 + 0.72 \sigma_{t-1}^2$

Optimal ARMA-GARCH Model for the Equal-weighted Index:

ARMA(1,2)-GARCH(1,1):

$r_t = 0.605 r_{t-1} + \varepsilon_t - 0.452 \varepsilon_{t-1} + 0.085 \varepsilon_{t-2}$

$\sigma_t^2 = 0.081 \varepsilon_{t-1}^2 + 0.648 \sigma_{t-1}^2$

Table 6

Descriptive Statistics of Market Shock Data (New Series of Changes)

Index Type	Mean	Median	Maximum	Minimum	Standard Deviation	Kurtosis Coefficient	Skewness Coefficient
Overall Index	0.025	-0.0076	4.18	-4.48	0.377	49.36	2.47
Equal-weighted Index	0.13	0.089	5.66	-4.87	0.440	46.05	1.71

As shown in Table 6, the mean of the overall index and the equal-weighted index are very close to each other. Additionally, the skewness coefficient (greater than zero) and kurtosis coefficient (greater than 3) in these indices indicate that the distribution of the series is not normal.

Figure 11 presents the time series plot of changes (market shock) for the combined ARMA(2,3)-GARCH(1,1) model for the overall index.

Figure 12 presents the time series plot of changes (market shock) for the combined ARMA(1,2)-GARCH(1,1) model for the equal-weighted index.

IJIMOB
E-ISSN: 3041-8992

Figure 11

New Series of Changes (Market Shock) for the Overall Index

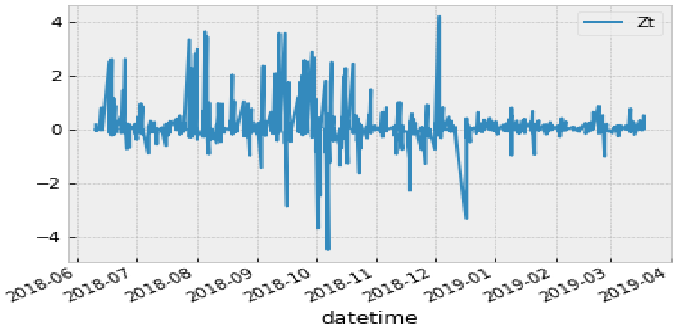
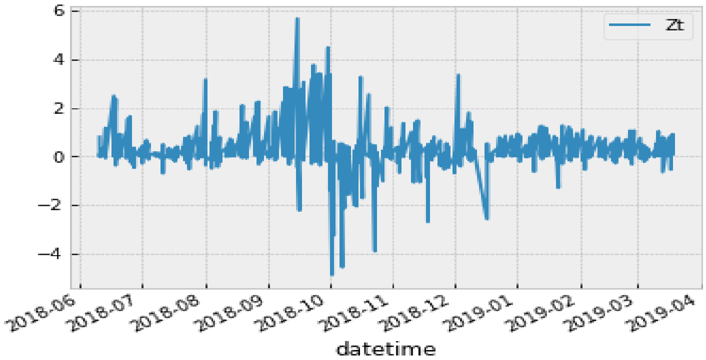


Figure 12

New Series of Changes (Market Shock) for the Equal-weighted Index



4 Discussion and Conclusion

The present study aimed to provide a model for estimating stock market shocks using the ARMA-GARCH model in the Tehran Stock Exchange. The statistical population of this research consisted of the overall index and the equal-weighted index, with the period from June 10, 2018, to March 18, 2019, for 15-minute intraday data (including 2,521 data points) selected as the statistical sample.

Excel software was used to organize data and perform preliminary calculations on raw data, while Python 3.9 software was employed for data analysis and model fitting to determine market shocks.

The input data to the conceptual model was the intraday logarithmic return series related to the 15-minute index from June 10, 2018, to March 18, 2019, with 2,521 data points for both the overall index and the equal-weighted index.

The results of descriptive statistics of intraday returns show that the mean of the overall index and the equal-weighted index are very close to each other. Additionally, the skewness and kurtosis coefficients in these indices indicate that the distribution of variables is not normal.

The results of the unit root test to examine the stationarity of intraday logarithmic returns show that based on the ADF and PP tests, since the test statistic for all three indices was greater than the critical value at the 1%, 5%, and 10% probability levels and prob < 0.05, the time series of returns for all three indices did not have a unit root and were stationary.

The purpose of this research was to use the ARMA-GARCH model to identify stock market shocks in the Tehran Stock Exchange. The ARMA-GARCH model was used in the conceptual model to identify and estimate stock market shocks. The input to the ARMA-GARCH model was the intraday logarithmic return series, which after analysis, the model order for both indices was determined based on the Akaike criterion.

Given the research question regarding the optimal model for estimating stock market shocks based on the ARMA-

IJIMOB
E-ISSN: 3041-8992

GARCH approach in Iran, as this research was conducted on two indices, the overall index and the equal-weighted index, the models presented for the two indices were different. For the overall index, the ARMA(2,3)-GARCH(1,1) model with 8 degrees of freedom was chosen, while for the equal-weighted index, the ARMA(1,2)-GARCH(1,1) model with 6 degrees of freedom was selected as the appropriate model. As observed, the ARMA model order was different for the indices, but the GARCH model order was the same for both indices, which answers the research question.

As indicated in the obtained results, the probability values for AC and PAC for both indices were less than 0.05, indicating that the new series of changes (stock market shocks) for both indices are completely random. Therefore, based on the specific objective of this research, stock market shocks for both the overall index and the equal-weighted index were estimated using the ARMA-GARCH model as a time series (new series of changes) and were found to be completely random and non-normal. The graphs for both the overall index and the equal-weighted index are displayed at the end of the findings.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

References

Abbasinejad, H., & Gudarzi Farahani, Y. (2014). Estimating the Degree of Integration in CPI with ARFIMA-FIGARCH Model: Case study of Iran. *Economics Research*, *14*(52), 26-21. https://joer.atu.ac.ir/article_133_en.html

Da, Z. H. I., Engelberg, J., & Gao, P. (2011). In Search of Attention. *The Journal of Finance*, *66*(5), 1461-1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x

Engle, R. (2002). New frontiers for arch models. *Journal of Applied Econometrics*, *17*(5), 425-446. https://doi.org/10.1002/jae.683

Engle, R. F., & Ng, V. K. (1993). Measuring and Testing the Impact of News on Volatility. *The Journal of Finance*, *48*(5), 1749-1778. https://doi.org/10.1111/j.1540-6261.1993.tb05127.x

Engle, R. F., & Russell, J. R. (1998). Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data. *Econometrica*, *66*(5), 1127-1162. https://doi.org/10.2307/2999632

Fabozzi, F. J., & Xiao, K. (2017). Explosive rents: The real estate market dynamics in exuberance. *The Quarterly Review of Economics and Finance*, *66*, 100-107. https://doi.org/10.1016/j.qref.2017.07.006

Fabozzi, F. J., & Xiao, K. (2019). The Timeline Estimation of Bubbles: The Case of Real Estate. *Real Estate Economics*, *47*(2), 564-594. https://doi.org/10.1111/1540-6229.12246

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5

Hirshleifer, D., & Shumway, T. (2003). Good Day Sunshine: Stock Returns and the Weather. *The Journal of Finance*, *58*(3), 1009-1032. https://doi.org/10.1111/1540-6261.00556

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics*, *12*(1), 13-32. https://doi.org/10.1016/0304-405X(83)90025-9

Kim, C.-W., & Park, J. (1994). Holiday Effects and Stock Returns: Further Evidence. *The Journal of Financial and Quantitative Analysis*, *29*(1), 145-157. https://doi.org/10.2307/2331196

Leung, A. C. M., Agarwal, A., Konana, P., & Kumar, A. (2016). Network Analysis of Search Dynamics: The Case of Stock Habitats. *Management Science*, *63*(8), 2667-2687. https://doi.org/10.1287/mnsc.2016.2470

Park, J., Konana, P., Gu, B., Kumar, A., & Raghunathan, R. (2013). Information Valuation and Confirmation Bias in Virtual Communities: Evidence from Stock Message Boards. *Information Systems Research*, *24*(4), 1050-1067. https://doi.org/10.1287/isre.2013.0492

Sun, J., Xiao, K., Liu, C., Zhou, W., & Xiong, H. (2019). Exploiting intra-day patterns for market shock prediction: A machine learning approach. *Expert Systems with Applications*, *127*, 272-281. https://www.sciencedirect.com/science/article/pii/S0957417419301599

IJIMOB

E-ISSN: 3041-8992

Xiao, K., Liu, Q., Liu, C., & Xiong, H. (2017). Price Shock Detection With an Influence-Based Model of Social Attention. *ACM Trans. Manage. Inf. Syst.*, *9*(1), Article 2. https://doi.org/10.1145/3131781

Zhang, L., Xiao, K., Liu, Q., Tao, Y., & Deng, Y. (2015, 14-17 Nov. 2015). Modeling Social Attention for Stock Analysis: An Influence Propagation Perspective. 2015 IEEE International Conference on Data Mining,

Zhang, L., Zhang, L., Xiao, K., & Liu, Q. (2016, 18-21 Aug. 2016). Forecasting price shocks with social attention and sentiment analysis. 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM),

IJIMOB
E-ISSN: 3041-8992