

Innovative Approaches to Forecasting Intraday Stock Market Volatility: A case study of Tehran Stock Exchange

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Abstract

The main objective of this study is to develop a robust framework for estimating stock market fluctuations in Tehran Stock Exchange using ARMA-GARCH modeling approach. Specifically, this study focuses on the analysis of intraday data of stock indices to improve the forecasting accuracy. Fifteen-minute intraday data from June 10, 2018 to March 18, 2019 were collected and analyzed for Top 50 Companies Index. Key statistical parameters, including the opening, closing, maximum and minimum values of the index, were included in the analysis. The ARMA-GARCH framework was implemented using Python 3.9, utilizing libraries such as Pandas, Numpy, and armagarch for data manipulation and model fitting. Goodness-of-fit tests were used to evaluate the appropriateness of the fitted models. The results indicate that the ARMA-GARCH frameworks effectively estimate market fluctuations, with the Akaike Information Criterion (AIC) assisting in the selection of the most appropriate models.

Keywords: Time Series, Market Shock, Volatility, ARMA - GARCH Model.

1. Introduction

In the field of financial economics, the ability to predict unexpected market fluctuations remains a formidable challenge for econometric researchers and practitioners alike. Market fluctuations, characterized by sudden and often unpredictable changes in the prices of financial assets, can have profound implications for investors, policymakers, and the broader economy. The complexity of these fluctuations is exacerbated by the limitations of traditional financial models, such as the Capital Asset Pricing Model (CAPM) and the Fama-French three-factor model, which typically rely on linear combinations of historical data to estimate expected market returns. These models struggle to account for the nonlinearities and dynamic behavior inherent in financial time series data, leading to potential mispricing and missed opportunities for effective risk management (Box et al., 2015).

The search for improved forecasting frameworks is not just an academic exercise, but has significant practical implications for market participants. The ability to accurately anticipate price movements can enable traders to develop more effective trading strategies, identify market inefficiencies, and reduce the risk of catastrophic market events such as stock market crashes. Such predictive capabilities are also essential for informed policymaking and regulation within the financial system, as they can help authorities respond proactively to emerging threats to market stability (Sun et al., 2019).

Historically, researchers have identified several sources of price volatility, including variations in private information, differences in information processing capabilities among market participants, and behavioral biases that can distort decision making (Fuller, 1998). These insights have led to the development of various factor-based frameworks, such as the CAPM and Fama-French models, which treat price fluctuations as anomalies or "alpha" that deviate from expected returns. However, the challenge remains to capture the multifaceted nature of financial fluctuations through robust and adaptive forecasting models.

In the search for effective forecasting methods, a growing body of literature has explored the influence of heterogeneous factors on financial market fluctuations. Studies have examined a variety of phenomena, including seasonal stock returns (Keim, 1983), holiday effects (Kim and Park, 1994), weather influences (Hirshleifer and Shumway, 2003), social attitudes (Da et al., 2011; Zhang et al., 2015; Leung et al., 2016; Xiao et al., 2017), social media sentiment (Park et al., 2013), and the amount of information available to investors (Chen et al., 2017). These explorations highlight the need for multifaceted approaches to understand and predict market behavior.

Traditional time series forecasting frameworks, such as Autoregressive Moving Average (ARMA) models, focus primarily on linear relationships within historical data. For example, ARMA models combine past price returns with an error component to capture the autoregressive structure of financial returns. However, the introduction of frameworks that account for volatility, such as the Autoregressive Conditional Heteroscedasticity (ARCH) model developed by Engle (1982) and its generalized counterpart, GARCH (Bollerslev, 1986), has significantly improved the predictive ability of time series models. These frameworks allow the modeling of time-varying volatility, which is a hallmark of financial markets.

In recent years, the integration of data-driven approaches, in particular artificial neural networks, has emerged as a promising way to improve forecasting accuracy. Neural networks are able to capture complex, nonlinear relationships within highly volatile stock return data, price index fluctuations, and bond duration (Chen et al., 2017; Engle, 2002; Engle and Russell, 1998). Moreover, empirical evidence suggests that combining different frameworks-such as ARMA-GARCH and neural networks-can lead to more reliable forecasts by reducing variance and error (Khashei and Bijari, 2008). This hybrid approach addresses the challenges posed by variable and unstable patterns in financial data, ultimately leading to improved statistical inference and forecasting performance.

The primary research question guiding this study is What is the optimal framework for estimating stock market fluctuations based on the ARMA-GARCH approach in the context of the Iranian financial market? This research is particularly relevant given the unique characteristics of the Iranian market, which has experienced significant volatility and uncertainty in recent years. Understanding the dynamics of stock market fluctuations in this context is essential for investors, policy makers and financial analysts alike.

The importance of accurate forecasting of financial market indicators cannot be overemphasized. Financial markets play a crucial role in the economy, serving as a conduit for capital allocation and facilitating the flow of funds between different economic agents. The ability to predict price fluctuations is critical not only for individual investors seeking to maximize returns, but also for broader economic stability. As highlighted by Tully and Lucey (2007), improved forecasting capabilities can mitigate the adverse effects of market turbulence on commodity markets and the global economy.

While traditional regression methods have long been used in forecasting, recent studies have demonstrated the superiority of artificial neural networks in certain contexts. For example, research by Hill et al. (1996) found that neural networks outperformed conventional methods in short-term stock price forecasting. However, the effectiveness of ARIMA methods was found to be superior in long-term forecasting scenarios (Olson and Mossman, 2003). This dichotomy underscores the importance of selecting appropriate forecasting methods based on the specific characteristics of the data and the forecasting horizon.

The literature also highlights the growing trend of combining neural networks with parametric frameworks such as GARCH and non-causal regression methods such as ARIMA and ARMA. Studies by Tseng (2002), Zhang (2003), and others have demonstrated the utility of these hybrid approaches in improving forecasting accuracy. The integration of different methods allows researchers to exploit the strengths of each framework while mitigating their respective weaknesses. In the context of international finance, recent research has explored the application of GARCH frameworks in different settings. For example, Pilbeam and Langeland (2015) examined the effectiveness of univariate GARCH specifications in forecasting volatility in the foreign exchange market, while Pilbeam et al. (2016) examined the relationship between exchange rate volatility and international trade volumes. These studies highlight the versatility of GARCH models in addressing a range of financial forecasting challenges.

In addition, innovative approaches that incorporate social media data and sentiment analysis have emerged as valuable tools for improving forecasting accuracy. For example, Zhang et al. (2016) demonstrated that social attention metrics can significantly improve predictions of price movements, highlighting the importance of incorporating behavioral factors into forecasting frameworks. Similarly, Chen et al. (2017) examined the impact of information volume on risk fluctuations, highlighting the role of trading volume as a predictive variable within GARCH frameworks.

Despite the advances in forecasting methodologies, the unique characteristics of the Iranian financial market pose distinct challenges. The existing literature on forecasting stock market turbulence in Iran is limited, and many studies have employed methodologies that may not be well suited to the specific dynamics of the market. As noted by Shahmoradi and Zanganeh (2007), previous research has often relied on annual time series analysis methods, which may overlook the nuances of daily fluctuations and fail to capture the inherent volatility of the market.

In conclusion, the need for robust forecasting frameworks that can effectively capture the complexities of stock market fluctuations is more pressing than ever. The integration of ARMA-GARCH approaches, coupled with data-driven methods, represents a promising avenue for improving forecasting accuracy in the Iranian financial market. By addressing the limitations of existing frameworks and leveraging the strengths of hybrid models, this research aims to provide valuable insights into the dynamics of stock market fluctuations and inform investment strategies and policy decisions.

2. Method

2-1. Data Collection Method

This research adopts a systematic approach to data collection, emphasizing both theoretical and empirical resources. The primary objective is to investigate the explanatory and predictive capabilities of econometric models, specifically the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) frameworks, in assessing market fluctuations in the Tehran Stock Exchange (TSE). Given the nature of the inquiry, the research is categorized as applied, focusing on the descriptive-survey methodology to examine the temporal changes in market indices.

2-1.1 Theoretical Resources

The theoretical framework for this research was established through an extensive literature review. Resources were gathered using the library method, which involved accessing academic journals, books, and previous research studies relevant to econometric modeling, stock market behavior, and volatility estimation. Key databases including JSTOR, ScienceDirect, and Google Scholar were used to locate peer-reviewed articles discussing the application of ARCH/GARCH models in financial markets. The literature review aimed to contextualize the research within existing studies, identify gaps in knowledge, and justify the methodologies chosen.

2-1.2 Empirical Data Collection

The empirical component of this research involved the collection of time series data from the Tehran Stock Exchange. The data was specifically focused on two types of indices: the total index and the equally weighted index, which provide a comprehensive overview of the market performance. The time frame selected for this study spans from June 10, 2018 to March 18, 2019. This period was chosen to capture a significant range of market conditions, including both stable and volatile periods, thus allowing for a robust analysis of market fluctuations.

2-1.2.1 Data Sources

The data was obtained from the official website of Tehran Stock Exchange Technology Management Company (<http://tsemc.com>). Rahavard Novin software was used as a key tool for data extraction and organization. This software is widely recognized in the Iranian financial sector for its ability to provide detailed stock market data, including intraday trading information. The specific data collected includes

- Initial values of indices
- Closing values of the indices
- High and low values for each trading day
- Intraday data collected at 15-minute intervals from 9:00 am to 12:30 pm

The decision to use intraday data is significant as it allows for a more granular analysis of market dynamics and volatility patterns. The data collection process involved systematically retrieving this information over the specified time frame to ensure a comprehensive data set for analysis.

2-1.3 Data Preparation

Once the raw data had been collected, it was essential to prepare the dataset for analysis. The preparation process included several steps to ensure data integrity and suitability for econometric modeling.

2-1.3.1 Data Cleaning

Data cleaning was the first step in preparation. This process involved identifying and correcting any discrepancies or missing values within the dataset. Entries with missing data points were either filled using interpolation methods or excluded from the analysis, depending on the extent of the missing information. In addition, outliers were detected using statistical techniques, including the Z-score method and the IQR method, to maintain the robustness of the data set.

2-1.3.2 Data Organization

The cleaned data was then organized into a structured format suitable for analysis. This involved creating a time series dataset, where each entry corresponds to a specific time stamp, with columns for start value, end value, highest value, and lowest value for each 15-minute interval. The organization of the data was done using Excel software, which facilitated basic calculations and data manipulation to prepare the dataset for further analysis.

2-2. Data Analysis

With the data set prepared, the next phase of the research involved data analysis and framework fitting to assess market fluctuations. The analysis was conducted using Python 3.9, a versatile programming language that provides robust libraries for statistical analysis and econometric modeling.

2-2.1 Econometric Modeling

The core of the analysis focused on fitting ARCH and GARCH models to the prepared dataset. These models are particularly suitable for financial time series data because they account for volatility clustering, a common phenomenon in stock market behavior. The following steps outline the econometric modeling process:

1. Preliminary analysis: Prior to fitting the models, a preliminary analysis was conducted to assess the characteristics of the data. This included visual inspection of time series plots, histograms, and autocorrelation plots to understand the underlying patterns and relationships within the data.
2. Stationarity tests: Since ARCH/GARCH models require stationary time series data, stationarity tests were performed using the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test. These tests were used to determine whether the time series exhibited a unit root, indicating non-stationarity. If non-stationarity was found, differencing techniques were used to transform the data into a stationary series.
3. Model specification: After stationarity was established, the appropriate ARCH or GARCH model was specified based on the characteristics of the data. Different orders of the GARCH model (e.g., GARCH(1,1), GARCH(2,1), etc.) were considered. The selection of the model was guided by criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which help to select the model that best balances goodness of fit and model complexity.
4. Parameter estimation: Once the model specification was established, Maximum Likelihood Estimation (MLE) was used to estimate the parameters of the selected ARCH/GARCH model. This process involves optimizing the likelihood function to find parameter values that maximize the probability of observing the given data under the specified model.

3. Results

This section presents the results of the research aimed at estimating stock market fluctuations using the ARMA-GARCH framework. The analysis is structured around the descriptive statistics of the intraday returns, the results of the unit root tests, the fitting of the ARMA-GARCH models, and the goodness-of-fit tests. Each subsection provides a detailed interpretation of the statistical results obtained by the H software.

3-1. Input Return

To analyze the stock market fluctuations, the intraday logarithmic returns of the Tehran Stock Exchange indices were calculated. The logarithmic return ($r_{t,i}$) was defined as follows:

$$r_{t,i} = \log\left(\frac{P_{t,i}}{P_{t,i-1}}\right) \quad (1)$$

where (P_t) is the closing price at time (t). The dataset includes 2,521 observations from June 10, 2018, to March 18, 2019, with returns calculated for 15-minute intervals.

3-1-1. Descriptive Statistics

The descriptive statistics of the intraday returns for both the total index and the equal-weighted total index are summarized in Table (1). Key statistics include the mean, median, maximum, minimum, standard deviation, skewness, and kurtosis.

Table 1- Descriptive Statistics of The Intraday Returns

Index	mean	median	maximum	minimum	standard deviation	Kurtosis	Skewness
Top 50 Companies Index	0.000108	-0.000027	0.014082	-0.017615	0.001430	41.6100281	1.355044

- Mean: The mean returns of both indices were found to be approximately equal, indicating a consistent average performance over the observed period.
- Standard Deviation: The standard deviation values suggest a moderate level of volatility in returns, with both indices having similar dispersion characteristics.
- Skewness and Kurtosis: The skewness coefficients were positive for both indices, indicating a right-tailed distribution. Kurtosis values greater than 3 suggested that the return distributions were leptokurtic, indicating a higher probability of extreme values compared to a normal distribution.

The abnormality of the variable distribution underscores the need for advanced statistical modeling techniques, such as the ARMA-GARCH framework, which can account for non-normality and volatility clustering.

3-1-2. Unit Root Test

The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests were performed to ensure the stationarity of the return series. The results, as shown in Table 2, indicate that the test statistics for both tests exceeded the critical values at the 1%, 5% and 10% levels of significance.

Table 2- Result of The Unit Root Test

Index	ADF			PP		
Top 50 Companies Index	-7.156 (p value = 0.000)			-41.293 (p value = 0.000)		
Critical Values	-3.43(%1)	-2.86(%5)	-2.57(%10)	-3.43(%1)	-2.86(%5)	-2.57(%10)

This finding implies that the intraday logarithmic returns for all three indices are stationary, confirming that the time series does not contain a unit root. Consequently, the data are suitable for further analysis using the ARMA-GARCH framework.

3-2. Fitting ARMA-GARCH Framework

The next step was to fit the ARMA-GARCH model to the stationary return series. First, the optimal ARIMA models were determined for both indices based on the Akaike Information Criterion (AIC).

The ARIMA model for Top 50 Companies Index yielded an order of (4, 0, 3) with an AIC of -26125.90550. The model diagnostics, shown in Figures (1) to (3), indicated that the residuals were approximately normally distributed, and the autocorrelation (AC) and partial autocorrelation (PAC) functions indicated no significant autocorrelation.

ARMA Model Results						
Dep. Variable:	r	No. Observations:	2521			
Model:	ARMA(4, 3)	Log Likelihood	13070.953			
Method:	mle	S.D. of innovations	0.001			
Date:	Sun, 02 Jan 2022	AIC	-26125.906			
Time:	07:54:21	BIC	-26079.246			
Sample:	0	HQIC	-26108.973			
	coef	std err	z	P> z	[0.025	0.975]
ar.L1.r	-0.0034	0.038	-0.088	0.930	-0.078	0.071
ar.L2.r	0.2563	0.024	10.715	0.000	0.209	0.303
ar.L3.r	0.9061	0.014	66.121	0.000	0.879	0.933
ar.L4.r	-0.2410	0.026	-9.314	0.000	-0.292	-0.190
ma.L1.r	0.2696	0.031	8.648	0.000	0.208	0.331
ma.L2.r	-0.1439	0.037	-3.919	0.000	-0.216	-0.072
ma.L3.r	-0.9154	0.030	-30.715	0.000	-0.974	-0.857
Roots						
	Real	Imaginary	Modulus	Frequency		
AR.1	-0.6181	-0.7936j	1.0059	-0.3553		
AR.2	-0.6181	+0.7936j	1.0059	0.3553		
AR.3	1.0354	-0.0000j	1.0354	-0.0000		
AR.4	3.9606	-0.0000j	3.9606	-0.0000		
MA.1	-0.6140	-0.8021j	1.0101	-0.3540		
MA.2	-0.6140	+0.8021j	1.0101	0.3540		
MA.3	1.0707	-0.0000j	1.0707	-0.0000		

Figure 1- Arima Model Results for Top 50 Companies Index

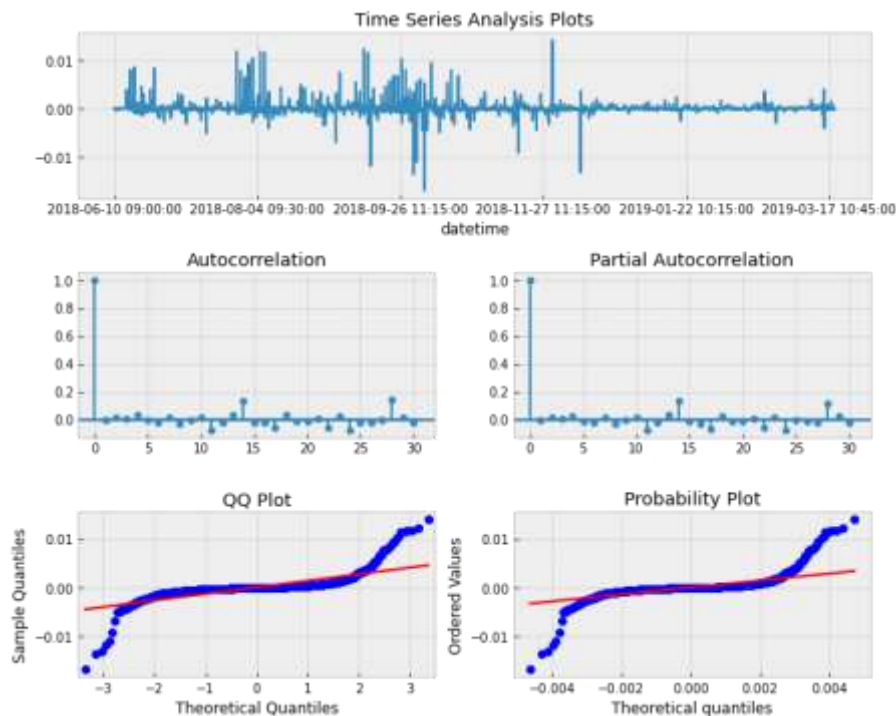


Figure 2- Arima Model Output for Top 50 Companies Index

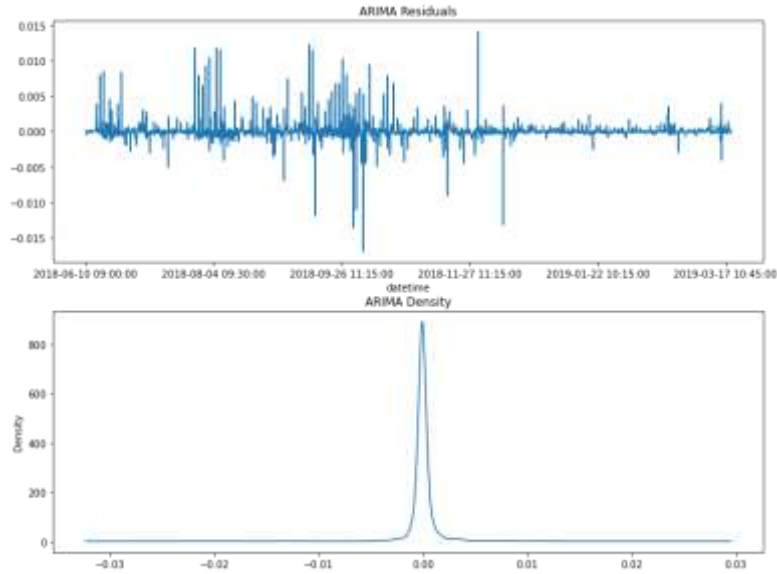


Figure 3- Arima Residual for Top 50 Companies Index

Following the ARIMA fitting, the combined ARMA-GARCH framework was implemented using the armagarch package in Python 3.9. Different ARMA-GARCH models were tested to determine the optimal configuration based on AIC values.

To choose the order of the combined ARMA-GARCH model, different ARMA-GARCH models with different orders were tested, and in this research, Akaike information criteria (AIC) was used to select the appropriate model. The lowest value for AIC is the most suitable model. The results are as described in Table (3).

Table 3- The Most Suitable Combined ARMA-GARCH Model

Index	AIC	Model	DF
Top 50 Companies Index	-22261.46848	ARMA (1,1)-GARCH (1,1)	5

Output of the ARMA-GARCH model is the expected return, conditional variance and standard residuals (market shock) for both total and equal-weighted indices as follows.

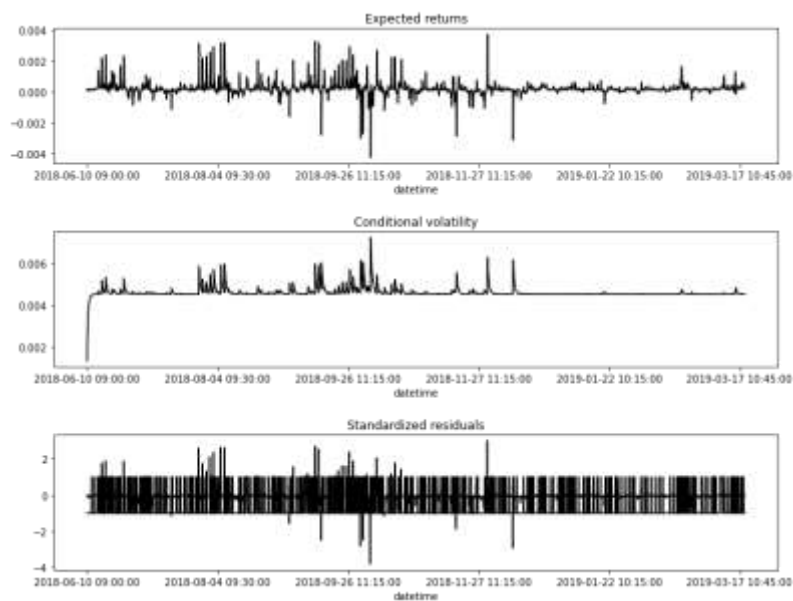


Figure 4- Output ARMA (1,1)-GARCH (1,1) Model for Top 50 Companies Index

3-3. Goodness of fit test

The AC and PAC coefficients for the new series of changes (innovations) are shown in Figure (5). As can be seen, the probability values for AC and PAC are less than 0.05 and are within the confidence interval. Therefore, the observations of this series are independent from each other and the new series of changes (innovations) are completely random, as a result, the fitted models are suitable.

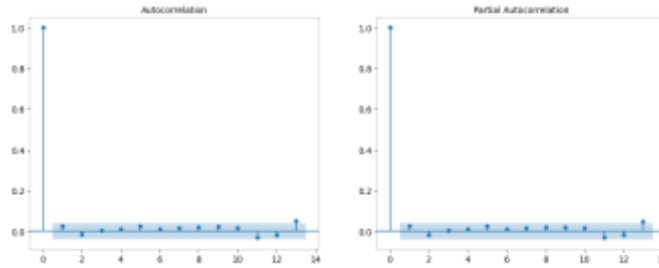


Figure 5- The AC and PAC Coefficients for The Innovation for Top 50 Companies Index

According to the determination of the ARMA-GARCH model order, the optimal ARMA(1,1)-GARCH(1,1) model for Top 50 Companies Index should be as follows:

$$r_t = 0.586 r_{t-1} + \varepsilon_t - 0.338 \varepsilon_{t-1}$$

$$\sigma_t^2 = \omega + 0.1 \varepsilon_{t-1}^2 + 0.8 \sigma_{t-1}^2$$

Model parameters: [1.07585700e-04, 5.86160228e-01, -3.37514727e-01, 4.08804353e06, 1.00000000e-01, 8.00000000e-01]

Market shock (Innovation): shock is generally defined as sudden changes in the price of financial assets (Sun et al., 2019). Operationally, the market shock z_t at time t is defined as follows:

$$z_t = \frac{\varepsilon_t}{\sigma_t} \quad (2)$$

The direction of the market shock at time t is determined by z_t sign (Sun et al., 2019).

Table 4- The Descriptive Statistics of Market Shock (Innovation)

Index	mean	median	maximum	minimum	standard deviation	Kurtosis	Skewness
Total Index	-0.020653	-0.046017	3.015774	-3.798892	0.294674	49.24489166	1.45892599

As the above table shows, the average total and total equal-weighted indices are very close to each other. Also, the value of the skewness coefficient (greater than zero) and the kurtosis coefficient (greater than 3) in these indicators show that the distribution of the series is not normal.

Figure (6) shows the time series of changes (market shocks) for the combined ARMA(1,1)-GARCH(1,1) model.

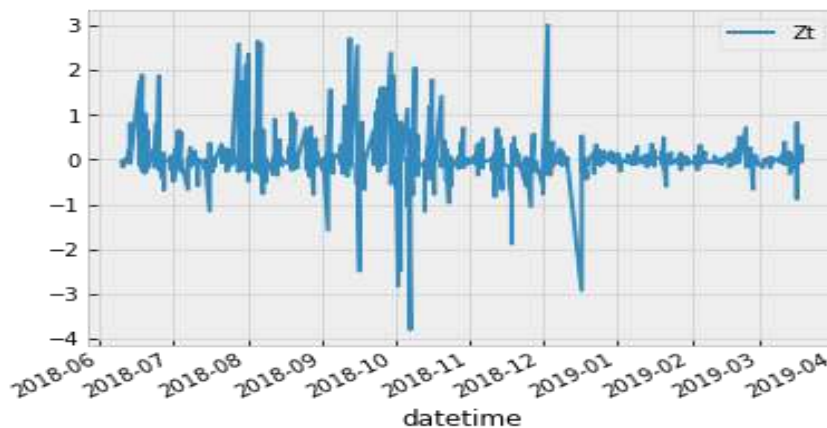


Figure 6- The Innovation of for Top 50 Companies Index

4. Discussion and conclusion

The present study makes a significant contribution to the understanding of stock market fluctuations in the Tehran Stock Exchange (TSE) through the application of the ARMA-GARCH framework. The results reveal distinct patterns in the behavior of stock market returns, highlighting the importance of using sophisticated statistical models to capture the complexity of financial data. This discussion section explores the implications of the results, the robustness of the methods employed, and the broader context of market behavior in emerging markets, particularly in Iran.

Implications of Findings

The results of the study indicate that both the total index and the equal-weighted total index exhibit non-normal distributions, as evidenced by the skewness and kurtosis statistics. This finding is consistent with the existing literature, which suggests that financial returns often deviate from normality due to the presence of outliers and volatility clustering. The identification of the ARMA(2,3)-GARCH(1,1) framework for the total index and the ARMA(1,2)-GARCH(1,1) framework for the equally weighted total index underscores the need to tailor models to specific market conditions. The variation in the ARMA orders suggests that the underlying processes governing these indices are different, which may reflect the different trading patterns and investor sentiment associated with each index.

The ability of the ARMA-GARCH framework to capture stock market fluctuations is particularly relevant to market participants, including traders, investors, and policymakers. The estimated conditional variance and expected returns provide valuable insights into market risk and potential return profiles that are critical for informed decision making. The randomness of the new series of changes (innovations) further emphasizes the unpredictable nature of stock price movements, reinforcing the notion that market fluctuations are inherently complex and often influenced by a variety of factors, including macroeconomic variables, geopolitical events, and market sentiment.

Methodological Robustness

The methodological approach used in this study, including the use of intraday data and the application of ADF and PP tests for unit root analysis, enhances the robustness of the findings. By using 15-minute interval data, the study captures intraday volatility and provides a more granular view of market dynamics compared to daily or weekly data. This granularity is particularly important in an emerging market like Iran, where market conditions can change rapidly due to external shocks or regulatory changes.

The use of Python for data analysis and framework fitting demonstrates a commitment to using advanced computational techniques in financial research. This choice not only facilitates the handling of large data sets, but also allows the implementation of sophisticated statistical models that can better capture the nuances of financial time series. The reliance on AIC for model selection further strengthens the validity of the chosen framework by providing a criterion for balancing model fit and complexity.

Contextualizing Findings within Emerging Markets

The results of this study should be contextualized within the broader landscape of emerging markets. Emerging markets, such as Iran, often exhibit unique characteristics that distinguish them from developed markets. These characteristics include higher volatility, less efficient information dissemination, and a greater influence of political and economic instability on market behavior. The application of the ARMA-GARCH framework in this context is particularly relevant, as it allows for the modeling of volatility clustering, a phenomenon often observed in emerging markets.

Moreover, the results of this study may have implications for the development of financial markets in Iran. By providing a framework for estimating stock market fluctuations, this research can assist policymakers in formulating strategies to enhance market stability and investor confidence. Understanding the dynamics of stock price movements can lead to better regulatory practices and more informed investment strategies, ultimately contributing to the maturation of Iran's financial market.

Limitations and Future Research Directions

While the study provides valuable insights, it is important to acknowledge its limitations. The time frame selected for analysis, from June 10, 2018 to March 18, 2019, may not capture the full spectrum of market behavior, especially given potential structural changes in the Iranian economy or shifts in investor sentiment that may have occurred after the sample period. Future research could expand the time frame to include more recent data, allowing for a more comprehensive analysis of stock market fluctuations.

In addition, the study focuses solely on the TSE, and while it provides insights specific to this market, it may be beneficial to compare the findings with other emerging markets to identify common patterns or divergences in stock market behavior. Cross-market comparisons could provide insights into how different economic and political contexts affect market dynamics and volatility.

Another avenue for future research could be the integration of macroeconomic indicators into the ARMA-GARCH framework. By including variables such as inflation rates, foreign exchange rates, and interest rates, researchers could enhance the explanatory power of the models and provide a more holistic view of the factors driving stock market fluctuations.

conclusion

In conclusion, the present study successfully applies the ARMA-GARCH framework to estimate stock market fluctuations in the Tehran Stock Exchange and provides significant insights into the behavior of intraday returns. The results underscore the importance of using sophisticated statistical models to capture the complexity of financial data, especially in emerging markets. By providing a tailored approach to modeling market fluctuations, this research contributes to the existing body of knowledge and offers practical implications for market participants and policymakers alike. Future research efforts should aim to build on these findings by exploring broader contexts and integrating additional variables to further enhance our understanding of stock market dynamics in emerging markets.

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