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Original Research Article

A Five-Minute Interval Analysis of High-Frequency Volatility under Information Asymmetry: Empirical Evidence from The Tehran Stock Exchange

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The modeling and forecasting of yield volatility in the Stock Market have become increasingly critical due to their pivotal role in key applications such as Value at Risk (VaR) assessment, optimal resource allocation in investment portfolios, effective investment management, and accurate pricing of derivatives. Among the key drivers of yield volatility, information asymmetry between market participants has emerged as a significant factor influencing market dynamics. Despite its importance, the empirical exploration of this phenomenon in emerging markets, particularly the Tehran Stock Exchange (TSE), remains scarce. This study examines the impact of information asymmetry on the volatility of the TSE's total index, employing the advanced Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (FIGARCH) framework. Intraday trading data from 2023 to 2024, collected at five-minute intervals, form the basis of this analysis. Information asymmetry was quantified via the transaction volume-weighted price impact metric. The Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC) determined the optimal model specification, leading to the application of FIGARCH, with exogenous information asymmetry incorporated into the GARCH (1,1) baseline model. Empirical results underscore a positive and statistically significant relationship between information asymmetry and return volatility in the TSE. These findings have profound implications for enhancing market efficiency, risk management, and derivative pricing strategies in emerging stock markets.

Keywords: Information Asymmetry, Return Volatility, Total index, Conditional Heteroskedasticity, GARCH, FIGARCH

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1 Introduction

One of the key factors in the stock market, which hinders the economic benefits from capital market investments, is uncertainty, or investment risk, primarily attributed to market volatility (Fang, 2012). Volatility refers to the degree of variation in the price of financial instruments over time. Therefore, managing risk begins with the optimal allocation of resources across various investment portfolios, followed by the accurate estimation of volatility. In risk management, two primary indicators must be considered: the return on an asset and the volatility of that asset (return risk) within the given investment timeframe.

If the goal is to achieve a certain return, investors must also be aware of the corresponding risk they are exposed to. Risk and return are interdependent elements that must be considered simultaneously in financial decision-making. One of the methods to operationalize risk measurement is the Value at Risk (VaR) index, widely used today to estimate financial and non-financial risks, including market, credit, and operational risks. To calculate VaR, it is necessary to first compute the conditional mean and variance of asset returns (Keshavarz Haddad, 2015). Effective risk management depends on the accuracy of volatility estimation models. True volatility, defined as an indicator of return risk based on asset price frequency data, is crucial for managing risk. Several models exist for predicting conditional variance (volatility) of assets, which refers to the conditional standard deviation of asset returns. Volatility modeling simplifies VaR calculation and enhances the parameter estimation efficiency and prediction accuracy (Maki and Ota, 2021).

Most methods for analyzing time series, such as maximum likelihood estimation, rely on regression models. While these models consider multiple exogenous factors, they have key limitations, particularly the assumption of homoscedasticity. The homoscedasticity assumption suggests that the estimated coefficients of regression models cannot be generalized to estimate true population parameters. Models that explain conditional variance changes (volatility) are referred to as conditional heteroskedastic models (Chen et al., 2019). Among the significant models are ARCH, GARCH, IGARCH, and FIGARCH models (Tayefi & Ramanathan, 2012). The ARCH and GARCH models are widely used for predicting volatility, especially when relying on daily, weekly, and monthly data, as they effectively model long memory in time series. Despite their simplicity, these models efficiently track volatility. Moreover, incorporating heteroscedasticity and non-conditional volatility modeling helps include market shocks (Chen et al., 2019). For stock market to operate efficiently, allocative, operational, and informational efficiency must be improved. Information symmetry plays a critical role in stock market, where data related to asset prices should be quickly and comprehensively reflected. This information symmetry supports fair pricing and optimal capital allocation, both at the corporate and industrial levels (Fattahi et al., 2017).

However, the presence of information asymmetry, where some market participants possess more or better-quality information than others, can lead to market inefficiencies. This imbalance can result in market failures, poor decisions (e.g., adverse selection), and moral hazard. Information asymmetry impacts both return volatility and overall market volatility. One example is the leverage effect, where negative returns in prior periods increase future volatility (Maki & Ota, 2021). Regulatory bodies must ensure information symmetry to prevent insider trading and protect shareholders' rights. However, the effect of information asymmetry on volatility in the Tehran Stock Exchange remains underexplored. Thus, this research investigates how information asymmetry affects the volatility of the Tehran Stock Exchange Total Index using FIGARCH models.

The FIGARCH model is chosen for this study due to its ability to incorporate exogenous variables (such as information asymmetry). It allows for a slow, hyperbolic decay of disturbances in conditional variance, effectively capturing long-memory behavior in financial volatility. Volatility (conditional variance) is essential for price discovery processes in derivatives and underlying assets. With the derivative market in Iran developing, this research aims to improve volatility forecasting models and lay the groundwork for optimal risk management in stock market.

1.1 Research Gap & Innovation

Despite the importance of information asymmetry in the stock market, no previous study has explored its impact on the volatility of the Tehran Stock Exchange Total Index using high-frequency data. This research employs conditional heteroskedasticity models, particularly FIGARCH, as an alternative to regression models. The advantage of these models over regression models is their ability to handle variance heteroscedasticity, which leads to biased estimates in traditional regressions. Furthermore, this study utilizes high-frequency data at 5-minute intervals, which is a novel approach in the context of an emerging market, offering insights distinct from those of developed markets. This research provides recommendations for improving the information infrastructure of the capital market and enhancing risk management in developing countries.

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1.2 Problem Statement

A significant challenge in financial risk management and resource allocation in stock markets is the volatility induced by information asymmetry. In the Tehran Stock Exchange, informational discrepancies shape market dynamics, leading to inefficiencies in asset pricing and portfolio management. This study aims to fill the gap by investigating how information asymmetry affects volatility in the Tehran Stock Exchange's Total Index using the FIGARCH model. By analyzing high-frequency data from 2023 to 2024, this research uncovers the real-time impact of asymmetric information on return volatility, providing valuable insights for investment strategies and risk management in emerging markets. The findings will contribute to improving the understanding of volatility dynamics, offering guidance for efficient resource allocation and policy recommendations to stabilize the market.

The structure of this paper is as follows: Section 2 provides an in-depth review of the theoretical background and literature, focusing on volatility modeling and its significance in stock market, with special emphasis on the Tehran Stock Exchange. Section 3, Methods & Design, elaborates on the research methodology and empirical analysis design. This section introduces the FIGARCH model, justifying its use for modeling long-memory volatility and the impact of information asymmetry on stock market volatility. It also discusses the data collection process, including the selection of variables and sources, and delves deeper into the estimation of models, underlying assumptions, and the specific techniques employed to ensure robust and reliable results. Section 4, Empirical Findings, presents the results of the empirical analysis, offering a thorough examination of how information asymmetry affects the volatility of the Tehran Stock Exchange index. The findings are presented alongside statistical significance tests, including coefficient estimates, p-values, and model diagnostics, followed by a detailed discussion comparing these results with existing literature and evaluating their consistency. Finally, Section 5, Conclusions & Discussions, synthesizes the main findings and discusses their implications in the stock market.

2 Literature Review

In the literature review, the theoretical foundations of volatility modeling are established, focusing on models such as ARCH, GARCH, and FIGARCH, which are used to understand the dynamics of financial volatility and its impact on asset prices. The choice of the FIGARCH model for this study is directly linked to its ability to capture long-memory effects, volatility clustering, and asymmetrical shocks, which are essential when modeling high-

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frequency data from the Tehran Stock Exchange. As the literature indicates, volatility patterns, particularly those influenced by information asymmetry, exhibit persistence over time, making the FIGARCH model particularly suitable for this research. The theoretical discussions of conditional variance and the influence of exogenous variables, such as information asymmetry, justify the adoption of FIGARCH, as it allows for the modeling of volatility using both past information and external variables. This connection between the theoretical foundations of volatility and the methodology of using FIGARCH for high-frequency data analysis directly addresses the research objectives of exploring the impact of information asymmetry on market volatility.

2.1 Volatility Measurement and Its Role in Financial Risk and Uncertainty

Generally, volatility is a statistical measure of the dispersion around the mean of any random variable, such as market parameters, etc. (Maki and Ota, 2021). Volatility in stock market refers to the volatility in the returns of the securities in question. In finance, volatility (typically denoted by σ) is the degree of change in a series of trading prices over time, usually measured by the standard deviation of the logarithmic returns. For a financial instrument whose price follows a Gaussian random walk or Wiener process, the width of the distribution increases with time. This is because, as time passes, the probability that the price of the instrument deviates further from its initial price increases. However, instead of increasing linearly, volatility increases with the square root of time as time increases, because some volatilities are expected to cancel each other out. Therefore, the most probable deviation after twice the time will not be twice the distance from zero. Volatility often refers to the degree of uncertainty or risk associated with the size of changes in the value of securities. Higher volatility means that the value of a security can potentially be spread over a wider range of values. This means that the price of the security can change significantly in either direction in a short period of time. When market makers infer the probability of an unfavorable selection, they adjust their trading ranges, which in turn increases the volatility band of the price. From one perspective, volatility is generally categorized into two types: realized volatility and implied volatility. Realized volatility measures the existence of volatility in a time series of past market prices, but implied volatility looks forward in time, as it is derived from the market price of a traded derivative in the market (especially an option). Volatility is often used to describe risk, but it is not always the case. Risk includes the chance of

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experiencing a loss, while volatility indicates how much and how quickly prices move. If these price increases also increase the probability of a loss, risk increases accordingly.

2.2 Insights from Market Microstructure: Linking Information Asymmetry to Market Volatility

The relationship between information asymmetry and volatility in the stock market has been widely explored within market microstructure theory, which examines how the structure of markets and the flow of information impact asset prices and volatility. According to this theory, markets with high levels of information asymmetry tend to experience greater price volatilities, as informed traders can exploit their advantage, leading to more significant and persistent volatility. In the context of high-frequency trading, the rapid dissemination and reaction to information can exacerbate these effects, as small informational imbalances can trigger substantial market movements.

Market microstructure theory specifically highlights the critical role of liquidity and order flow in the transmission of volatility. In markets where information is unevenly distributed, liquidity providers, such as market makers, face increased uncertainty in pricing assets, which results in wider bid-ask spreads as a compensation for the risk they assume. This dynamic increases the cost of trading for uninformed market participants, amplifying volatility by reducing trading activity and exacerbating price movements. Moreover, informed traders' actions, driven by superior information, not only affect market prices directly but also influence the behavior of uninformed traders, creating a feedback loop. This strategic behavior of informed traders, coupled with the information cascades they create, causes price distortions and amplifies volatility clustering, a hallmark of volatility in stock market. Additionally, under market conditions where the dissemination of information is highly rapid, such as in high-frequency trading environments, even small asymmetries in information can lead to large, unpredictable price shifts, reinforcing market instability. The complexity of these interactions within market microstructure theory underscores how information asymmetry, when coupled with market structure inefficiencies, creates a self-reinforcing cycle that heightens volatility and disrupts market equilibrium, particularly in more fragmented or less liquid markets.

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2.3 ARCH and GARCH Models: Tools for Modeling Volatility in Stock Market

Volatility is a measure of uncertainty, playing a crucial role in financial theories, risk management, and option pricing. Volatility is the conditional variance of asset price changes, which is not directly observable and is considered a hidden variable, calculated indirectly using approximations. Two general approaches in financial economics literature are used to model and calculate volatility. In the first approach, conditional variance is modeled as a function of the squared shocks of past asset returns. GARCH models fall into this category. In the conditional density function, the conditional mean and variance of returns must be used to write the likelihood function of the observations. The conditional distribution of a return has a conditional heteroscedastic variance, and considering this characteristic leads to the achievement of efficient maximum likelihood estimators. Furthermore, one of the conditions for the adequacy of regression models is that the error components of the model should be white noise (without serial autocorrelation). Another condition for the adequacy of regression models is that there should be a non-linear relationship between the error components. Situations may arise where the error components of the model do not possess these characteristics. This means that the error components face the problem of conditional heteroscedasticity, autoregressive conditional heteroscedasticity (ARCH). To account for this non-linear information present in the error components of regression models, ARCH models in their generalized form (GARCH) are a suitable and important analytical tool. Models used in predicting volatility (volatilities) of returns in stock market play a crucial role in calculating Value at Risk (VaR), optimal portfolio allocation models, investment management, and derivative pricing (Muchnik, et al., 2009). Volatility models also consider the correlation in the squared returns (conditional variance or volatility) and incorporate it into model building and the parameter estimation process (Ryu, et al., 2022). In other words, if the log returns are white noise, there is no reason for their squared values (volatility) to also be white noise. The squared return represents the second-order moment of the return; therefore, if it is not white noise, it indicates the existence of conditional variance heterogeneity, given past information in the return time series.

One of the most widely used and effective models for predicting volatility and volatilities is the Autoregressive Conditional Heteroscedasticity (ARCH) model, and its generalized form (GARCH). Conditional autoregressive models, using daily, weekly, and monthly data, and employing parameters that

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indicate long-term memory in time series, effectively model and analyze volatilities. Moreover, despite their simplicity and ability to track volatilities, conditional autoregressive models effectively model volatility with high efficiency and effectiveness. Furthermore, modeling volatility using non-conditional heteroscedasticity methods allows for modeling abrupt jumps and shocks in the stock market by considering jump elements in the model (Chen et al., 2019). Some of the most important models in this family, widely used in theoretical foundations and previous research, include the Autoregressive Conditional Heteroskedasticity (ARCH) model, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, the Integrated GARCH (IGARCH) model, and the Fractionally Integrated GARCH (FIGARCH) model (Tayefi & Ramanathan., 2012). Generally, in the ARCH framework, it is assumed that large shocks are followed by large shocks, and similarly, small shocks are followed by small shocks, which is known as volatility clustering. While the ARCH model is simple, it often requires many parameters to adequately describe the volatility process of asset returns. Therefore, several alternative models have been introduced. Engle and Bollerslev (1986) introduced the generalized ARCH model. The GARCH model is an infinite-order ARCH with exponentially decreasing weights for distant lags. If the AR polynomial in the GARCH model has a unit root, we will have an integrated GARCH (IGARCH) model, which was first introduced by Engle and Bollerslev (1986). One of the key features of the IGARCH model is that the impact of past squared shocks is persistent, and the pricing of risky securities, including long-term options and futures contracts, may exhibit strong dependence on initial conditions (Maki & Ota, 2021).

2.4 The FIGARCH Approach

Empirical studies using FIGARCH models (Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity) support the notion that information asymmetry significantly influences long-term volatility patterns in markets characterized by informational inefficiencies. Research by Sivakumar and Mohandas (2009), Haque and Farzana (2021), and others highlights the persistence of volatility in such settings, with informed traders adjusting their positions based on asymmetric information, further amplifying market volatility. For the TSE, where market inefficiencies and information gaps are particularly pronounced, these theories suggest that volatility is not solely driven by external factors but is deeply intertwined with the market's response to asymmetrically distributed information. Consequently, reducing information asymmetry through enhanced

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transparency and improved regulatory frameworks could mitigate these volatility effects, fostering greater market stability and efficiency.

Several studies have reported long-term memory in the autocorrelation of squared or absolute values of various financial assets. Following these observations, Baillie et al., (1996) introduced the Fractionally Integrated GARCH (FIGARCH) model, a generalization of the integrated conditional heteroscedasticity (IGARCH) process. The initial objective of introducing the FIGARCH model was to develop a more flexible model for conditional variances, capable of explaining and representing the observed temporal dependencies in stock market volatility, and to capture the impact of external variables (lateral variables) on return volatility. Specifically, the FIGARCH model allows only a slow, decreasing hyperbolic rate for the squared or absolute components of the error term in the conditional variance function. This model can accommodate the temporal dependency of the variance and the leptokurtic unconditional distribution of returns with long-memory behavior for the conditional variances. Based on the above information, the FIGARCH model's advantage and preference over other conditional autoregressive models lies in the ability to use exogenous variables alongside error components and previous periods' values for the variable of interest (return volatility) (Chen et al., 2019).

2.5 Efficient Market Hypothesis and the Impact of Information Asymmetry on Stock Market

Generally, investors' goal from buying shares is to gain returns, and in this regard, one of the most important needs of investors in the stock exchange is to have the necessary information about the optimal method of buying and selling shares. The efficient market hypothesis, relying on investors' rational use of all available information, claims that prices can accurately reflect all available information, and price changes in such a market are random and unpredictable over time. Informational efficiency means that information affecting the value of assets is equally and appropriately available to all market participants, and specific investors cannot benefit from informational rent to obtain more profits (returns in excess of risk-adjusted returns). Free flow of information, timely and transparent disclosure, lack of interference by investment institutions or regulatory and enforcement bodies, and... are the most important prerequisites for achieving informational efficiency (Karbasy Yazdy et al., 2015). According to the efficient market hypothesis, the performance of each portfolio of shares is independent of its past performance, and in situations where the market loses its efficiency relatively, appropriate

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investment strategies can be used to increase investment returns and achieve abnormal returns. The market efficiency discussion is generally examined in the framework of two related hypotheses: the random walk and the efficient market. The random walk states that prices are completely random, while according to the efficient market hypothesis, there are no opportunities to earn abnormal returns in excess of the risk taken in the market. Based on these two hypotheses, price behavior is random and does not follow a specific trend. In fact, price behavior is a function of a process called a random walk. The opposite of the efficient market hypothesis is information asymmetry. Information asymmetry is a condition in which traders and market players do not have the same information; in other words, one or more groups of individuals or legal entities have more information about the asset in question compared to other participants (Muchnik et. al., 2009).

2.6 The Role of Information Asymmetry in Stock Market & Research Hypothesis

Asymmetric information, the source of moral hazard, is one example of incomplete information; therefore, despite moral hazard, market output will not be optimal, which means market failure. Achieving optimal output requires addressing moral hazard. To do this, the agent's incentives must be changed so that, despite asymmetric information, the agent exerts the optimal level of effort. A tool that a principal can use to influence an agent's incentives is a contract. Asymmetric information means that one party to a transaction possesses information that the other party does not, and obtaining that information is costly. In economic literature, the issue of information asymmetry is usually categorized into two major groups. The first group encompasses situations where one party to an exchange is unaware of the other party's information, even though that information could affect their decision. This group is known as hidden information. The second group relates to situations where one party to a transaction undertakes actions that are hidden from the other party, but which also affect the other party's welfare. This group is referred to as hidden action. Moral hazard and adverse selection are two common issues in information economics. The former is related to hidden action, and the latter to hidden information. The difference between moral hazard and adverse selection is that in adverse selection, information asymmetry exists at the time of contract formation, whereas in moral hazard, information asymmetry exists after the contract is formed. Even in cases where information asymmetry does not exist at the time of contract formation, the contracting parties often expect information asymmetry to arise sometime

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after the contract is formed. Studies by Chen et. al., (2019), and Maki & Ota (2021) identified information asymmetry as one of the sources and influential factors in the volatility (volatility of returns) in stock market. In their view, information asymmetry among market participants prevents shareholders from gaining a proper understanding of the macroeconomic situation, industry, and strategies of publicly traded companies. As the market moves toward information asymmetry, access and trust in the information of capital markets face challenges, and decision-making is affected.

Information asymmetry, through various mechanisms, can influence volatilities in stock market. One such mechanism is leveraging effects, where negative returns on financial assets in previous days or periods can increase volatility in the time series of returns in subsequent periods (Maki & Ota, 2021). Findings from studies indicate that information asymmetry, in addition to increasing volatility in the time series of returns, also increases the probability of negative returns in future periods. Negative stock returns, like a lever, exacerbate and accelerate future return volatilities. Naturally, in highly efficient stock market, particularly in terms of information, the price and returns of stocks and other traded financial assets are highly sensitive to new news and information, financial and economic crises, and market changes. In information-efficient markets, information asymmetry manifests as an increase in the gap between bid and ask prices (suggested prices for buying and selling financial assets), thereby increasing volatility in the return time series (Ryu et al., 2022). Based on theoretical foundations and the research background, the following hypothesis can be formulated: Information asymmetry has a significant impact on the volatility of the Tehran Stock Exchange Index**.**

2.7 Research Background

Haddad & Samidi. (2009) estimated and predicted volatility in the Tehran Stock Exchange market and compared the accuracy of methods for estimating Value at Risk. Their results showed that the FIGARCH model provided the best fit and the best results for out-of-sample estimations. Komijani et al., (2012) compared various conditional heteroskedasticity models for modeling and forecasting volatility in oil prices. Based on information criteria and MSE, the FIGARCH model was selected as the best model for modeling and forecasting volatilities in Iranian heavy crude oil prices during the study period. Daman Keshideh & Nazmi Pilehroud., (2013) investigated the impact of inflationary uncertainty on the Tehran Stock Exchange's overall index using the FIGARCH method. The results of the model fit indicate that inflation rates

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and the consumer price index have a direct and significant impact on the Tehran Stock Exchange index. Paul et al., (2024) in a study, re-examined the economic growth in the shadow of financial stress in times of crisis: evidence from FIGARCH and wavelet coherence approach. The findings shows that the financial stress is having a prodigious effect on the economic growth of select economies. From the data analysis, it is found that the long-memory effect is noted in the gross domestic product (GDP) for India and Korea only, which implies that the volatility in the GDP series for these two nations demonstrates persistence and dependency on previous values over a lengthy period. Lotfalipour et al., (2017) used the FIGARCH method to measure conditional Value at Risk for portfolios in the Tehran Stock Exchange. The results indicated the presence of long-term memory in the time series of the Tehran Stock Exchange's overall index returns. Rostami & Makiyan., (2020) modeled stock return volatility using symmetrical and asymmetrical nonlinear state-space models in the Tehran Stock Exchange. The findings, in both symmetrical and asymmetrical models, reflect the high stability of the volatility waves generated by shocks to stock returns. Therefore, due to this high stability, the Tehran Stock Exchange market return changes are predictable.

Sivakumar & Mohandas., (2009) modeled and predicted stock returns using conditional variance FIGARCH models. Combining multiple factors or models allowed for the modeling and prediction of long-term dependencies in financial market volatility. Results indicated that FIGARCH models have high capability for modeling volatility in financial markets.

Cochran et al., (2012) examined stability in the time series of returns for base metals using the conditional variance model FIGARCH. Results showed FIGARCH adequately describes volatility processes, as all long-memory parameters were statistically significant. Bentes (2015) investigated the predictability of gold returns using FIGARCH models. The study used three GARCH models to analyze the behavior of gold return volatility. Results indicated that FIGARCH was the best model for measuring and modeling linear dependence in the conditional variance of gold returns, as shown by information criteria. FIGARCH was also the best model for predicting gold return volatility, allowing for the use of exogenous variables and political risks. Makki and Ota (2021) investigated the impact of information asymmetry on the volatility of real stock returns in the Japanese stock market, using Heterogeneous Autoregressive (HAR) models. Results showed the HAR model with leverage effect performed best among asymmetric models. Haque & Farzana (2021) modeled and predicted the return of the stock market

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index in Bangladesh, investigating long-term memory in this time series using the FIGARCH model. Results showed that using FIGARCH, or the fractional integrated generalized autoregressive conditional heteroskedasticity (FIGARCH) model, for conditional volatility modeling of stock returns had better performance in the estimation parameters compared to other GARCH families. Kyriakou et al., (2023) examined the impact of the real estate market on volatility in financial markets in developed countries (England, Germany, Australia, Japan, and the USA) using the FIGARCH model. Chen et al., (2022) investigated the predictive power of the conditional variance Heteroskedasticity FIGARCH model in estimating and modeling the volatility of the S&P 500 index returns. The results indicate that FIGARCH models performed better than GARCH models in modeling long memory in volatility. It was also found that the FIGARCH model is more sensitive to changes in volatility periods. Gupta & Mittal., (2024) modeled the long memory dependence structure using FIGARCH copula approach - evidence from major Asian stock markets. Aliyu et al., (2023) used FIGARCH models in a study to statistically model the volatilities in the Naira exchange rate per dollar. Their study examined the presence of long memory in both the mean and volatility of the Naira exchange rate per dollar series using fractional autoregressive integrated moving average (ARFIMA) models, generalized autoregressive conditional heteroskedasticity (GARCH), and fractional generalized autoregressive conditional heteroskedasticity (FIGARCH) models. The results show that the FIGARCH model performs better.

2.8 Conceptual Model of Information Asymmetry

This conceptual model (Figure 1) illustrates how information asymmetry directly influences the conditional variance of the total index of the Tehran Stock Exchange. Given the persistent nature of volatility in financial time series, volatility in market uncertainty due to asymmetric information are likely to sustain over time, amplifying price instability and investor risk. The model is structured based on empirical findings that confirm the statistically significant relationship between these two factors.

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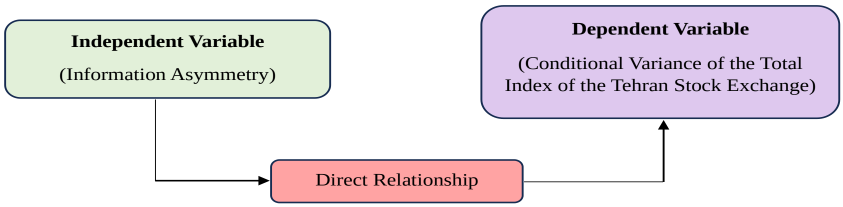

Figure 1. Conceptual model of research
Source: Research finding

3 Methods & Design

From a target perspective, this research is an applied study from the field of developmental studies. The results of this research can be used in calculating Value at Risk (VaR), pricing call and put options, and so on. Methodologically, this research falls into the category of descriptive-correlational research. The reasoning of this research is of the deductive type (from general to specific). Considering the correlational nature of the research subject and the measurability and operationalizability of the variables, the best method for conducting this research is the use of quantitative (parametric) research methods. In this method, first, the research variables are calculated, and then the relationships between these variables are examined and evaluated using advanced prediction models of return volatility of the Tehran Stock Exchange Total Index (integrated GARCH model). The spatial scope of this research is the Tehran Stock Exchange, and its time horizon is longitudinal (years 2023 & 2024), and the type of data is time series. In this research, volatility of return refers to historical real volatility, which is also called realized volatility. The reason for choosing this type of volatility is that although it is not directly observable in returns, the volatility of returns of various assets has the following common characteristics (Keshavarz Haddad, 2015): They are clustered – volatility does not tend to infinity; it changes within a limited, defined range and is stationary. It does not react symmetrically to large increases and decreases in asset prices. One of the characteristics of volatility in stock returns is that it is not directly observable. For example, calculating daily volatility with a single observation of asset return is not possible. However, if we have intraday data, then it is possible to calculate volatility. In this research, following Maki and Ota (2021), the logarithm of the Tehran Stock Exchange Total Index is used to calculate the return; however, since calculating volatility requires intraday data, the total

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index is used at 5-minute intervals (t = 5 minutes). In other words, the return variable of the Tehran Stock Exchange Total Index is calculated using equation 1 below:

$$R_t = ln_{(p_t)} - ln_{(p_{t-1})} \tag{1}$$

The total index value at time t is denoted by Pt, and the total index value 5 minutes prior to time t is denoted by p_{t-1}. The return on the total index for the first 5 minutes of trading each day is calculated relative to the total index value at the close of the previous trading day. However, the research variable of interest is the volatility of the return. Volatility (V) is defined as the conditional variance of the return, and is equal to the square of the logarithmic return, i.e.:

$$\mathrm{V} = R_t^2 \tag{2}$$

In this study, to model and predict the volatility of the Tehran Stock Exchange's overall index return, the exogenous variable of information asymmetry has been used. Information asymmetry arises when one or more investors possess private information about the value of a company. In markets with information asymmetry, investors or shareholders are concerned about trading with individuals and actors possessing information. Therefore, information asymmetry, from the perspective of the uninformed investor, is considered a risk factor, and for this reason, uninformed investors tend to quickly remove shares with private information from their portfolios (Chen et al., 2022). Based on theoretical analyses, information asymmetry is associated with a decrease in the number of traders, a decrease in transaction volume, high transaction costs, a large difference between the bid and ask prices, and low marketability of securities. According to Amihud (2002), the price impact represents the percentage change in price resulting from each dollar of stock transaction. Based on this indicator, the higher the price impact, the greater the information asymmetry; because information asymmetry causes transaction costs. In such a case, market makers, due to potential hidden costs, provide lower marketability for the stocks. To measure information asymmetry using the price impact function of the Tehran Stock Exchange's overall index, relationship 3 has been used.

$$\mathrm{ASYM} = \frac{1}{D}\sum_{d=1}^{D_n}\frac{[r_i,d,t]}{V_i,d,t} \tag{3}$$

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In this research, ASYM represents the price impact of the Tehran Stock Exchange Total Index, approximating information asymmetry. r_i, d, t represents the return rate of the Tehran Stock Exchange Total Index at time t, and V_i, d, t represents the real volume of transactions at time t. D_n indicates the number of trading periods, calculated based on five-minute intraday data for a day. Intraday data on the total index, trading volume, and other necessary variables are collected from the Tehran Stock Exchange website, the Iranian Financial Information Processing Center, or the Information Technology and Communications Department of the Tehran Securities and Exchange Organization. Therefore, the overall data collection method is archival (Documentary). In this research, sampling methods typically used in panel data based on year-company observations are not relevant, because the primary data needed for this research is time series data (intraday index return and information regarding uncertainty estimation). In two years, with 477 trading days and 3.5 hours of market activity each day, with 12 five-minute intervals per hour, a total of 20,034 intraday observations were obtained. After measuring, calculating, and classifying research variables, a conditional heteroscedasticity model is used to test the research hypothesis. This model allows for the use of an exogenous variable (information asymmetry). Searches among conditional variance Heteroskedasticity models indicate that a model with these capabilities is a fractional integrated generalized autoregressive conditional heteroscedasticity (FIGARCH) model. In this study, volatility of returns refers to the conditional heteroscedastic variance of the time series of returns of the Tehran Stock Exchange Total Index. To test the research hypothesis, the following steps are taken in the analysis of data and modeling of conditional heteroscedasticity using the FIGARCH method (all necessary calculations are performed in EVIEWS).

First, the overall trend of the Tehran Stock Exchange's total index return time series is analyzed using descriptive tools (median, mean, standard deviation, trend analysis chart, etc.). One of the features examined in this section is the distribution shape of the logarithmic return of the Tehran Stock Exchange's total index based on intraday data. To examine the normality of the volatility variable of the total index return, the Jarque-Bera statistic is used at a 5% significance level. To use the FIGARCH model, the volatility time series (squared return) must exhibit long-term memory. In other words, if the volatility return trend chart does not show a very sharp and steep downward trend, it possesses hyperbolic function characteristics, indicating long-term memory (persistence or persistence of shocks). To examine long-term memory in the time series under study, in addition to the chart (intuitive

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understanding), the ACF and PACF functions of the time series can also be used. The autocorrelation (Autocorrelation) and partial autocorrelation (Partial Autocorrelation) of the total index return time series are examined using the Ljung-Box test. Autocorrelation of a time series is a mathematical tool for finding repeating patterns (such as the presence of an oscillating signal in noise), or identifying a specific frequency in a signal with harmonic frequencies. In statistics, the autocorrelation of a random process describes the correlation of process values at different times as a two-variable function (time and time shift), or a single-variable function (time shift). If X is a repeatable process and i is a point in time after the start of the process (i is an integer for a discrete-time process or a real number for a continuous-time process), then Xi is the value of that process (data) at time i. The Ljung-Box (Box-Ljung) test is a corrected form of the Portmanteau test and is used to examine the independence (uncorrelatedness) of time series. The statistic of this test is defined to equation 4.

$$Q = n\sum_{t-1}^{m} r_i^2 \sim \chi_m^2 \tag{4}$$

In the above context, n represents the number of observations, m the time lag value, and r_{i} denotes the $i-th$ correlation coefficient between variables X_{t} and $X_{\mathrm{t+1}}$. The null hypothesis in this test is that $r_1 = r_2 = \ldots = r_{\mathrm{i}} = 0$. The alternative hypothesis is that $r_{\mathrm{i}} \neq 0$. The modified Ljung-Box statistic performs better than other autocorrelation statistics such as the Box-Pierce statistic.

Next, the stationary status of the closing return of the main index (based on intraday data) must be examined. For this purpose, the Augmented Dickey-Fuller (ADF) unit root test is used, and if the closing return time series is not stationary, the first-order difference of it is used. A random process is called strictly stationary if its properties do not change with a change in the time origin. In practice, checking this condition is difficult, and therefore we use the weak assumption. In econometrics, in general, a white noise variable is a variable with an unpredictable structure, whose past behavior cannot be generalized to the future. The stationarity condition of a variable with a time series is that the roots of its interpreting equation lie outside the unit circle (Engle & Granger, 1987). After examining autocorrelation, partial autocorrelation, and stationarity of the time series return, the ARCH effect test should be performed. For this purpose, the ML technique, or McLeod & Li (1983), is used. The null hypothesis of this test is the absence of ARCH effects. If the significance level of this test is less than 5%, the null hypothesis is

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rejected, and ARCH effects are present in the time series of closing returns of the Tehran Stock Exchange based on intraday data. As an alternative solution, Lagrange multipliers can also be used. If the Lagrange statistic is greater than the critical value of the chi-squared (χ^2) sample function, the null hypothesis of no conditional heteroscedasticity is rejected, and the alternative hypothesis, which is the presence of ARCH or conditional heteroscedasticity in the variance, is accepted. After confirming the existence of ARCH effects, the existence of GARCH effects in the return time series must also be ensured. This should also be done in order to calculate the width of the Intercept, the lagged values of the shock and past values of the variance. The GARCH effects test is first examined with Auto-regression (AR) and moving mean (MA) equal to 1, i.e. GARCH (1,1), and then other order values are used to achieve the best value. After the GARCH models are applied, the optimal model, which has the lowest interruption rate (Akaike (AIC), Schwarz and Hanen), is selected and the effects of ARCH are re-examined using the maximum likelihood technique. Thus, the best GARCH model for estimating the volatility of the total index yield of the Tehran Stock Exchange is obtained. As mentioned, the best and most optimal GARCH is the one that has the lowest error rate. AIC, BIC and Likelihood are used to ensure good performance of the conditional asymmetry model (volatility). The lower the BIC and AIC indicators and the higher the Likelihood indicator, the higher the quality of its performance. After determining the arch-GARCH binary model, using the FIGARCH model, the effect of the information asymmetry exogenous variable on the volatility of the total index yield is measured according to the optimal GARCH model and according to the coefficients obtained, the hypothesis is tested. In GARCH models, the focus is on how these models in estimating volatility in some way consider exogenous shocks in modeling. In other words, we assume that the exogenous variables/variables affect volatility (conditional variances). This variable in the present study is information asymmetry. The general GARCH equation with GARCH interruption (1,1) is then estimated as relation 5.

$$\partial_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \partial_{t-1}^2 + \delta_1 ASYM_t \tag{5}$$

Where the return volatility variable (intra-day logarithmic return component) ∂_t^2 is placed as a dependent variable of the components of the pre-period disruption (Ɛ), the values of volatility in the pre-period ∂_{t-1}^2 and the information asymmetry variable ($ASYM_t$) of the current period. After ensuring that all of the above conditions are met, the above-mentioned

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GARCH model is estimated in the maximum display method, or ML. The outputs of this model will be displayed in two parts: conditional mean and conditional variance. If the probability statistics corresponding to the conditional mean coefficients (AR and MA) are less than 5%, the yield per period is predictable in a coefficient of the yield of the previous period and the shock of the previous period. The information provided in the conditional variance section also shows the degree of association of current period volatilities with the previous periods. If the statistic of the corresponding probability of the information asymmetry variable is less than the significance level, the research hypothesis is confirmed and otherwise rejected.

3.1 Rationale for Adopting the FIGARCH Model in High-Frequency Volatility Forecasting

The application of FIGARCH models in this study, which employs high-frequency (5-minute interval) data from the Tehran Stock Exchange (TSE), is driven by the need to accurately capture the intricate dynamics of volatility at very granular time scales. High-frequency data, by its nature, provides a much finer resolution of market movements, which allows for the detection of volatility patterns that may not be observable in daily or lower-frequency data. In such a setting, FIGARCH emerges as an optimal model due to its ability to account for long-memory effects, volatility clustering, and asymmetric shocks over short time intervals, making it especially suitable for markets like the TSE, where informational inefficiencies and persistent volatility patterns are pronounced.

3.2 The Superiority of FIGARCH in Capturing Long-Memory and Volatility Clustering in Stock Market

High-frequency data, often characterized by 5-minute intervals in this study, is fundamentally different from lower-frequency data due to its higher noise-to-signal ratio and the potential presence of microstructure effects, short-term dynamics caused by market frictions, liquidity constraints, or informational asymmetry. These features complicate volatility modeling, as conventional models like GARCH fail to capture the fine-grained persistence in volatility observed in high-frequency data. The FIGARCH model, developed by Baillie et al. (1996), extends the GARCH family by incorporating long-memory processes, which are particularly crucial for capturing volatility persistence, a phenomenon where past shocks to volatility continue to influence future volatility for prolonged periods, even at very short time horizons.

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3.3 Strengths of the FIGARCH Model in High-Frequency Contexts

3.3.1 Long-memory Effects

One of the primary advantages of the FIGARCH model is its ability to model long-memory processes, which is essential when working with high-frequency data. stock market, especially those exhibiting persistent volatility clusters, can show long-term dependence in volatility even at minute intervals (Baillie et al., 1996). The long-memory feature of the FIGARCH model allows for the accurate modeling of volatility patterns at high frequencies, which are often invisible in models assuming short-memory processes.

This model can capture the temporal dependence of variance and the unconditional leptokurtic distribution for returns with long-memory behavior for conditional variances. The superiority of the FIGARCH model over other conditional heteroskedasticity autoregressive models lies in its ability to use exogenous variables alongside shock components and previous period values for the variable of interest (return volatility) (Chen et al., 2019).

3.3.2 Volatility Clustering

A critical feature of high-frequency data is volatility clustering, where periods of high volatility tend to follow other periods of high volatility, and periods of low volatility follow periods of low volatility. FIGARCH is particularly adept at capturing this clustering at high frequencies. As Chen et al. (2022) demonstrated, the ability to account for this clustering provides more accurate volatility forecasts, which are particularly crucial for risk management in high-frequency trading environments, where volatility spikes can significantly affect trading strategies and asset pricing.

3.3.3 Improved Forecasting Power

The FIGARCH model's superior forecasting capabilities are well-suited for markets characterized by persistent volatility and microstructure effects. High-frequency data is inherently subject to market noise, but the FIGARCH model has been shown to improve volatility forecasts in environments with high informational inefficiencies, making it ideal for the stock market such as the TSE. This enhanced forecasting ability is essential for risk management models such as Value-at-Risk (VaR), where accurate predictions of future volatility are crucial for managing potential risks in real-time trading scenarios (Chkili et al., 2012).

3.4 Limitations of the FIGARCH Model in High-Frequency Data

Despite its advantages, the FIGARCH model is not without limitations when applied to high-frequency data:

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3.4.1 Computational Complexity

The FIGARCH model's inclusion of long-memory terms and exogenous variables leads to increased computational burden, particularly when estimating parameters at high-frequency intervals. As a result, estimation can be time-consuming, and the model may require sophisticated optimization algorithms, especially when handling large datasets with high-frequency (5-minute) data.

3.4.2 Risk of Overfitting

The FIGARCH model's flexibility particularly in incorporating multiple exogenous variables may lead to overfitting, especially when the data is highly granular, like the high-frequency data in this study. Overfitting can reduce the generalizability of the model’s predictions to out-of-sample data, a common pitfall when working with high-frequency time series.

3.4.3 Microstructure Effects and Noise Sensitivity

High-frequency data often contains substantial market microstructure noise due to factors such as bid-ask spreads, market impact, and liquidity. While the FIGARCH model can capture volatility clustering and long-memory effects, it may still be sensitive to this microstructure noise, potentially leading to biased estimates unless proper filtering or noise-reduction techniques are applied.

Given the high-frequency nature of the data used in this study (5-minute intervals), FIGARCH is the most appropriate model for capturing the nuanced volatility patterns observed in the TSE. The TSE is particularly prone to informational asymmetry, where market participants may have unequal access to information, resulting in volatility clustering and persistence, which can span over very short time intervals. As Chen et al. (2022) have shown, the FIGARCH model performs exceptionally well in such environments by modeling persistent volatility patterns

Moreover, the high-frequency data from the TSE offers a highly detailed view of market dynamics that would be missed by lower-frequency models. The ability of FIGARCH to effectively model volatility clustering and long-memory effects is very important.

4 Empirical Findings

In this section, the variable volatility of returns is first examined in the data related to the total index of the Tehran Stock Exchange; then, using the FIGARCH model, the research hypothesis test and the study of the effects of information asymmetry on the volatility of returns are taken. Figure 2 shows

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the variable yield trend of the total index of the Tehran Stock Exchange at intervals of 5 minutes during the 2023 & 2024.

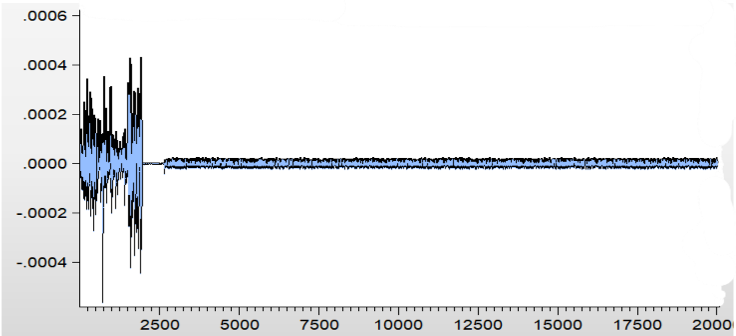

Figure 2. Total index return trend based on intraday data
Source: Research finding

As can be seen in Figure 3, in the early 2023, the total index yield was higher and its volatility gradually decreased. Another feature examined in this section is the form of the logarithmic return distribution of the total index of the Tehran Stock Exchange based on intraday data. To examine the variable normality of the total index yield volatility, the Jarque-Bera for statistic is used at a significance level of 5%. Figure 3 shows the state of the logarithmic return distribution of the total index intraday.

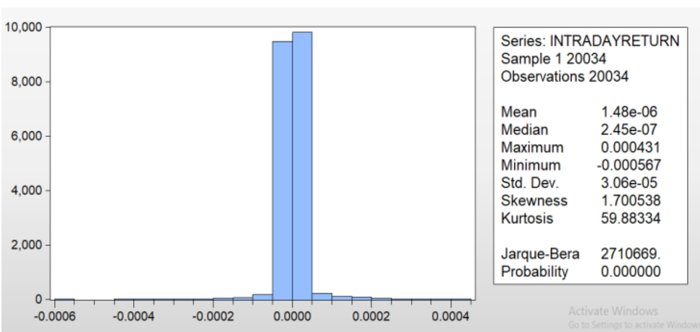

Figure 3. Normality status (distribution) of the logarithmic return variable of the total index
Source: Research finding

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Since the probability of this test is exceeds 5%, the variable in question does not have a normal distribution. Of course, the normality/absence of the distribution form is not a prerequisite and does not affect the modeling of asymmetric variance. Figure 4 also shows the logarithmic return of the total index of the Tehran Stock Exchange during the research period.

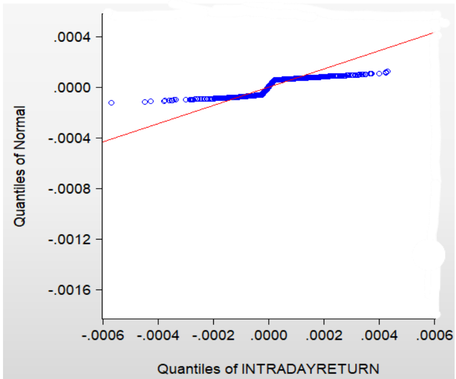

Figure 4. Quantiles of intraday returns
Source: Research finding

As can be seen in Figure 4, the logarithmic return of the total index of the Tehran Stock Exchange is based on intra-day data without normal distribution and is more elongated. Figure 5 also shows a Box Graph of the logarithmic efficiency variable of the total index:

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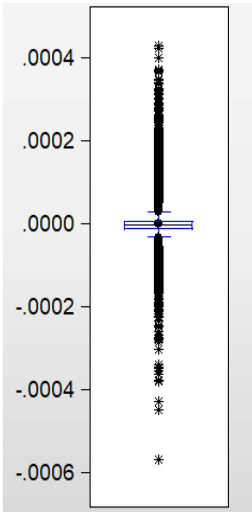

Figure 5. Box Graph of total index returns based on intraday data
Source: Research finding

As Figure 5 shows, the majority of logarithmic efficiency observations are scattered around the zero axis. In general, the results obtained in this section indicate that the logarithmic return time series of the total index of the Tehran Stock Exchange based on intraday data of a fluctuating time series has an average and trend and has a stationary. In order to be able to use the FIGARCH model, the time series of volatility (yield component) must have long-term memory. Table 1 shows the logarithmic return of the total index of the Tehran Stock Exchange using intraday data.

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Table 1

The autocorrelation and partial autocorrelation function of the logarithmic return time series

lag	**AC**	**PAC**	**Q-Statistic**	**Prob**	**lag**	**PAC**	**Q-Statistic**	**Prob**	**AC**
1	0.264	0.264	1400.8	0.000	19	0.040	0.002	3841.0	0.000
2	0.102	0.035	1611.0	0.000	20	0.013	-0.020	3844.3	0.000
3	0.168	0.143	2176.7	0.000	21	0.035	0.020	3868.6	0.000
4	0.091	0.012	2341.7	0.000	22	0.056	0.022	3930.9	0.000
5	0.061	0.023	2416.7	0.000	23	0.044	0.009	3970.6	0.000
6	0.043	-0.002	2454.6	0.000	24	0.084	0.055	4113.5	0.000
7	0.076	0.054	2569.1	0.000	25	0.100	0.044	4313.7	0.000
8	0.026	-0.020	2582.7	0.000	26	0.042	-0.021	4349.9	0.000
9	0.055	0.047	2643.6	0.000	27	0.081	0.048	4481.7	0.000
10	0.109	0.073	2879.9	0.000	28	0.067	0.002	4570.9	0.000
11	0.052	0.000	2933.1	0.000	29	0.041	0.005	4603.9	0.000
12	0.103	0.078	3145.8	0.000	30	0.055	0.024	4665.5	0.000
13	0.124	0.059	3452.1	0.000	31	0.073	0.031	4772.1	0.000
14	0.092	0.031	3622.4	0.000	32	0.046	-0.001	4814.5	0.000
15	0.058	-0.003	3689.9	0.000	33	-0.008	-0.040	4815.7	0.000
16	0.045	-0.004	3730.7	0.000	34	0.035	0.010	4839.8	0.000
17	0.041	-0.002	3765.0	0.000	35	0.057	0.023	4905.2	0.000
18	0.047	0.025	3809.5	0.000	36	0.053	0.026	4961.6	0.000

Note: AC = Autocorrelation, PAC = Partial Autocorrelation, Prob = Probability values. Sample size: 20034. Included Observation: 20034. Date: 07/02/23 Time: 19:01.

Source: Research finding

The autocorrelation status of this variable has been calculated using the Ljung-Box autocorrelation test for 36 lags. The null hypothesis in this test is the absence of autocorrelation of the variable. According to Table 1, since the corresponding probability statistic of each lag is less than 5%, the logarithmic return variable of the total stock exchange index is autocorrelated in all lags. At this stage, the reliability status of the total index return variable (based on intraday data) should be examined. For this purpose, the unit root test using the Augmented Dickey-Fuller (ADF) method is used. The null hypothesis in this test is the existence of a unit root (non stationarity). Table 2 shows the results of the reliability (stationarity) test of the logarithmic return variable.

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Table 2
Stationarity of logarithmic returns using intraday data

	T-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-17.80020	0.0000
Test critical values:		
1% level	-3.958493	
5% level	-3.410027	
10% level	-3.126736	

Note: The Augmented Dickey-Fuller test is used to test for the presence of a unit root in a time series. A significant p-value (Prob.*) indicates that the null hypothesis of a unit root can be rejected, suggesting the series is stationary.
Source: Research finding

As shown in Table 2, since the obtained significance level is less than 5% (close to zero), the null hypothesis is rejected, meaning that the time series is stationary; therefore, the logarithmic return variable has a stationary characteristic (width from the intercept and trend) and confirms the previous results; therefore, there is no need to use differencing in modeling the volatility of logarithmic returns. After examining the autocorrelation, partial autocorrelation, and stationarity of the return time series, a test for the existence of ARCH effects should be performed. For this purpose, the ML technique or McLeod and Li (1983) is used. The null hypothesis of this test is the absence of ARCH effects. If the significance level of this test is less than 5%, the null hypothesis is rejected and there are ARCH effects in the return time series of the Tehran Stock Exchange total index based on intraday data. Table 3 shows the results of fitting the logarithmic return model of the stock market index using the width from the intercept, time trend, and past values. As can be seen, this variable is affected by past values, width from the origin, and trend.

Table 3
Logarithmic efficiency fitting using past values, width from origin and trend

Variable	Coefficient	Std. Error	T-Statistic	Prob.
INTRADAYRETURN (-1)	0.264412	1.78E-18	1.49E+17	0.0000
C	1.09E-06	5.45E-23	2.00E+16	0.0000
T	1.000000	1.84E-18	5.43E+17	0.0000

Note: The results presented in this table summarize the regression analysis performed on the dataset. All variables are statistically significant at the 1% level, as indicated by their p-values (Prob.). The high t-Statistics values further confirm the strong relationship between the independent variables and the dependent variable. These results are consistent with theoretical expectations and align with prior literature in financial econometrics.
Source: Research finding

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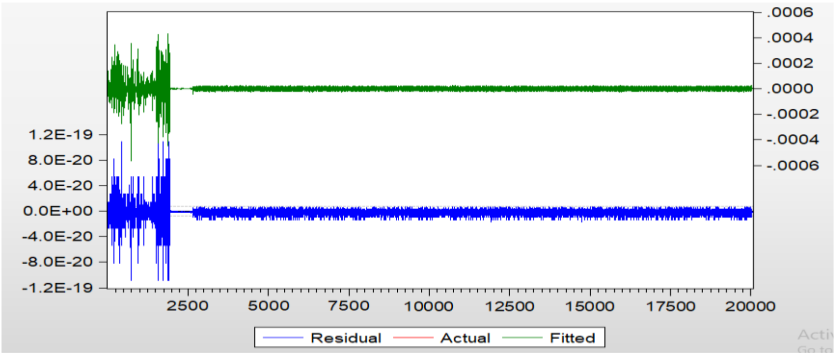

Figure 6. Residuals plot of the regression model of the logarithmic return variable with past values
Source: Research finding

Figure 6 shows the autocorrelation plot of the residuals of the above regression model. As can be seen, the presence of ARCH effects can be intuitively understood because the residuals of the regression model are autocorrelated.

Table 4
Results of the test for the existence of ARCH effects

Heteroskedasticity Test			
Metric	Value	Test Statistic	Prob.
F-statistic	3597.616	Prob. F (1,20030)	0.0000
Obs*R-squared	3050.136	Prob. Chi-Square (1)	0.0000

Source: Research finding

In order to be more certain of the autocorrelation in the residuals of the regression model, the ML maximum likelihood technique was used. The null hypothesis of this test is the absence of Arch effects. Table 4 shows the results of this test:

Since the significance level obtained for this test is less than 5%, the null hypothesis is rejected and the existence of ARCH effects is confirmed. Now that the existence of ARCH effects has been confirmed, the existence of GARCH effects must be checked. After confirming the existence of ARCH effects, the existence of GARCH effects in the return time series must also be checked. For this purpose, the GARCH model must also be fitted so that the width from the origin, the past values of the disturbance terms and the past

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values of the variance can be calculated. The test for the existence of GARCH effects is first examined with autoregression (AR) and a moving average (MA) equal to 1, that is, GARCH (1,1), and then other orders of fitting are also used to achieve the best fit. Table 5 shows the results of fitting the GARCH model with lags (GARCH (1,1)).

Table 5
GARCH model fitting results (GARCH (1,1))

GARCH Model: C (4) + C (5) * RESID (-1)^2 + C (6) * GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**Z-Statistic**	**Prob.**
INTRADAYRETURN (-1)	0.990974	0.004815	205.8041	0.0000
C	19.51849	9.939641	1.963701	0.0496
T	0.014118	0.005913	2.387666	0.0170
Variance Equation				
C	22.24261	2.635593	8.439320	0.0000
RESID (-1)^2	0.256640	0.024290	10.56550	0.0000
GARCH (-1)	0.724109	0.022749	31.83008	0.0000
R-squared	1.000000	Mean dependent var		1.48E-06
Adjusted R-squared	1.000000	S.D. dependent var		3.06E-05
S.E. of regression	1.39E-20	Akaike info criterion		8.783830
Sum squared resid	3.87E-36	Schwarz criterion		8.781463
Log likelihood	889309.2	Hannan-Quinn criter.		8.783056
Durbin-Watson stat	1.495815			

Note:
1. The table above reports the results of a GARCH (1,1) model estimation.
2. INTRADAYRETURN (-1) represents the lagged return, showing high persistence in the return series.
3. The variance equation includes RESID(-1)^2 (the lagged squared residual) and GARCH(-1) (the lagged conditional variance), both of which are statistically significant.
4. The model achieves high R-squared and Adjusted R-squared values, indicative of excellent fit.
5. The log-likelihood value is 889309.2, suggesting strong support for the model.
6. All probabilities (Prob.) below 0.05 denote statistical significance at the 5% level.
Source: Research finding

As can be seen, the coefficients of the width from the origin, the past values of the disturbance terms and the past values of the volatilities (disturbances) all have significant coefficients and as a result, it can be said that the model in question has a good predictive power and can predict, model and calculate the volatilities of the logarithmic yield well. In order to ensure that the GARCH model (GARCH (1,1)) is the best fit, other orders of fit (GARCH (2,2),

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GARCH (3,3), GARCH (4,4)) were also used, the results of the variance equation of which are presented in Tables 6 to 8.

Table 6
Variance equation fitting the GARCH (2,2)

Variance Equation				
Variable	**Coefficient**	**Standard Error**	**T-Statistic**	**P-Value**
C	1.31E-40	1.28E-18	1.03E-22	1.0000
RESID (-1)^2	0.120000	0.006400	18.75024	0.0000
RESID (-2)^2	0.040000	0.007533	5.309890	0.0000
GARCH (-1)	0.480000	0.038621	12.42831	0.0000
GARCH (-2)	0.040000	0.035922	1.113535	0.2655

Source: Research finding

Table 7
Variance equation fitting the GARCH (3,3)

Variance Equation				
Variable	**Coefficient**	**Standard Error**	**T-Statistic**	**P-Value**
C	1.35E-40	1.29E-18	1.05E-22	1.0000
RESID (-1)^2	0.100000	0.005407	18.49423	0.0000
RESID (-2)^2	0.033333	0.012710	2.622631	0.0087
RESID (-3)^2	0.033333	0.013061	2.552184	0.0107
GARCH (-1)	0.400000	0.112579	3.553055	0.0004
GARCH (-2)	0.033333	0.197553	0.168731	0.8660
GARCH (-3)	0.033333	0.088380	0.377160	0.7061

Source: Research finding

Table 8
Variance equation of the fitted GARCH (4,4)

Variance Equation				
Variable	**Coefficient**	**Standard Error**	**T-Statistic**	**P-Value**
C	1.38E-40	1.24E-18	1.11E-22	1.0000
RESID (-1)^2	0.085714	0.004715	18.17765	0.0000
RESID (-2)^2	0.028571	0.013672	2.089724	0.0366
RESID (-3)^2	0.028571	0.016278	1.755227	0.0792
RESID (-4)^2	0.028571	0.011245	2.548082	0.0111
GARCH (-1)	0.342857	0.143061	2.396586	0.0165
GARCH (-2)	0.028571	0.259963	0.109906	0.9125
GARCH (-3)	0.028571	0.230202	0.124114	0.9012
GARCH (-4)	0.028571	0.097638	0.292627	0.7698

Source: Research finding

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As can be seen, as the number of interruptions increases, the impaired sentences remain meaningful, but the past values of the volatilities of the previous two periods and the width of the origin are not meaningful, so the GARCH (2,2) has less predictive power for the variable volatilities than the GARCH (1,1). Likewise other asymmetric interruptions (2,1), (1,2), (3,2), (2,3) have also been used, and in none of them are all the width coefficients from the intercept, past values of the components of the disorder and past values of the volatilities were meaningless at the same time. After the GARCH models are applied, the optimal model, which has the lowest interruption rate (Akaike (AIC), Schwarz and Hanen), is selected and the effects of ARCH are re-examined using the maximum likelihood technique. Thus, the best GARCH model for estimating the volatility of the total index yield of the Tehran Stock Exchange is obtained. As mentioned, the best and most optimal GARCH is the one that has the lowest error rate. AIC, BIC and Likelihood are used to ensure good performance of the conditional asymmetry model (volatility). The lower the BIC and AIC indicators and the higher the Likelihood indicator, the higher the quality of its performance. For this purpose, the GARCH (1,1) is also reapplied using the TGARCH method, i.e. taking into account the threshold (1). Table 9 shows the results of the GARCH (1,1) by the GARCH threshold method. Since the criterion for selecting the optimal model is the lower indicators of AIC, Schwarz and Hanen, these coefficients should be compared in two models. Based on the data obtained from the comparison of Tables 11 and 7, it is concluded that the GARCH (1,1) has higher predictive power to model and estimate the logarithmic returns of the total index of the Tehran Stock Exchange using intraday data.

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Table 9

Results of fitting the GARCH (1,1) model with threshold

GARCH Model: C (4) + C (5) * RESID (-1)^2 + C (6) * RESID (-1)^2 * (RESID (-1) < 0) + C (7) * GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**Z-Statistic**	**Prob**
INTRADAYRETURN (-1)	0.264412	4.53E-07	583994.1	0.0000
C	1.09E-06	6.31E-10	1729.766	0.0000
T	1.000000	1.18E-06	844005.4	0.0000
Variance Equation				
C	21.93096	2.257352	9.715348	0.0000
RESID (-1)^2	0.150000	0.001097	13.63736	0.0000
RESID(-1)^2*(RESID(-1) < 0)	0.050000	0.013374	3.738663	0.0002
GARCH (-1)	0.600000	0.010445	57.44198	0.0000
R-squared	1.000000	Mean Dependent Var		1.48E-06
Adjusted R-squared	1.000000	S.D. Dependent Var		3.06E-05
S.E. of regression	1.39E-20	Akaike info criterion		8.789029
Sum squared resid	3.87E-36	Schwarz criterion		8.786267
Log likelihood	889362.3	Hannan-Quinn criterion		8.788125
Durbin-Watson stat	1.495815			

Notes:

1. Mean Equation: The INTRADAYRETURN (-1) coefficient (0.264412) is highly significant ($p < 0.0000$), indicating a strong positive relationship between current and lagged intraday returns. The constant term (C) is significant but small, reflecting negligible baseline effects. The time trend (T) highlights systematic growth in returns.

2. Variance Equation: The constant term (C) in variance is significant (21.93096) and establishes the baseline level of volatility. ARCH effects (RESID (-1)^2, 0.150000) indicate that lagged squared residuals influence current conditional variance. The asymmetric effect (RESID(-1)^2*(RESID(-1) < 0), 0.050000) confirms that negative shocks contribute disproportionately to volatility. The GARCH term (GARCH (-1), 0.600000) indicates strong volatility persistence.

3. Model Fit: The model exhibits excellent fit metrics (R^2 = 1.0, adjusted R^2 = 1.0). Information criteria values (AIC, SC, HQ) confirm its efficiency and parsimony.

4. Durbin-Watson Statistic: The Durbin-Watson statistic (1.495815) suggests no significant autocorrelation in residuals.

Source: Research finding

Next, it is necessary to ensure that the GARCH (1,1) model is free of variance heteroskedasticity among the disturbance components. For this purpose, the LM test is used. The null hypothesis in this test is the absence of variance heteroskedasticity. The results obtained are presented in Table 10.

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Table 10
Homogeneity of variance test of GARCH model (1,1)

Heteroskedasticity Test: ARCH		
Statistic	**Value**	**Prob**
F-statistic	2.047017	0.1526
Obs*R-squared	2.046980	0.1525

Source: Research finding

According to Table 11 information, the GARCH (1,1) lacks variance asymmetry; as it does not have ARCH effects. The final result is that the interruption criteria in the GARCH Model (1,1) are more optimal, and finally the GARCH Model (1,1) is selected as the final model of predicting and explaining the logarithmic returns of the Total Stock Exchange index based on intra-day data. After determining the optimal model of predicting the volatility of the Total Return Index of the Tehran Stock Exchange, the optimal model in question should be validated (1,1) using the FIGARCH approach by considering the information asymmetry variable on the volatility of the Total Return Index in order to confirm/reject the hypothesis in question according to the coefficients obtained. As mentioned, in GARCH models, the focus is on how these models in estimating volatility in some way consider exogenous shocks in modeling. In other words, we assume that the exogenous variables/variables affect volatility (conditional variances). This variable in the present study is information asymmetry. The general GARCH equation with GARCH interruption (1,1) is then estimated as relation 5. The results of the GARCH Model (1,1) with the information asymmetry bronze variable are presented in Table 11.

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Table 11

Results of fitting the GARCH (1,1) model with the exogenous variable of information asymmetry

GARCH Model: C (4) + C (5) * RESID (-1)^2 + C (6) * GARCH (-1) + C (7) * ASYMMETRY

Variable	**Coefficient**	**Standard Error**	**Z-Statistic**	**P-Value**
INTRADAYRETURN (-1)	-0.311834	0.028472	-10.95228	0.0000
AR (1)	1.592696	0.072625	21.93045	0.0000
MA (1)	0.966102	0.000940	1027.803	0.0000
Variance Equation				
C	-1.54E-13	1.40E-14	-11.01901	0.0000
RESID (-1)^2	0.198937	0.004198	47.38936	0.0000
GARCH (-1)	0.452246	0.005852	77.28375	0.0000
ASYMMETRY	0.113377	0.001255	90.33089	0.0000

Note:

1. The Mean Equation estimates the relationship between the intraday return, autoregressive, and moving average components. The significant INTRADAYRETURN (-1) coefficient suggests a negative impact of lagged returns on the current period's mean returns.
2. The Variance Equation employs a GARCH (1,1) framework to capture volatility clustering, with an asymmetric term (ASYMMETRY) to account for leverage effects. A positive and statistically significant ASYMMETRY coefficient highlights the asymmetrical behavior of volatility.
3. All coefficients are statistically significant at the 1% level (p-value < 0.01), indicating robust model estimation.
4. The very high z-statistics for most variables reflect the model's strong explanatory power in both the mean and variance equations.
5. Despite the negative constant term (C = -1.54E-13), it does not indicate an error in the model. The small magnitude (close to zero) reflects the specific dynamics of the Tehran Stock Exchange and does not affect the overall model's performance or the validity of the research hypothesis.

Source: Research finding

As can be seen in Table 13, the volatility values are significantly influenced by previous volatility, as the coefficients obtained for all three interrupt variables are less than 5%. The variance equation of Table 11 should be considered to examine the research hypothesis. As can be seen, the meaningful level corresponding to the information asymmetry variable is 0.0000, and since it is less than 5%, the information asymmetry variable has a positive and meaningful effect on the volatilities in the yield of the total index of the Tehran Stock Exchange, and therefore the research hypothesis is confirmed. The coefficient obtained for this variable is 11.34%, which indicates that on average, 11% of the volatilities in the total index of the Tehran Stock Exchange were affected by information asymmetry. Also, since the coefficients obtained for the variables of the disturbance and interruption

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components of the GARCH are less than 1, it can be concluded that in the estimated model, the volatilities in the index of the entire stock exchange are enduring. Since the sum of the coefficients obtained for the variable of the disturbance components and the GARCH interruption variable is also a number smaller than one, the persistence of volatility in the total index return time series is confirmed, meaning that the effect of the occurrence of a volatility in this pattern lasts until later periods.

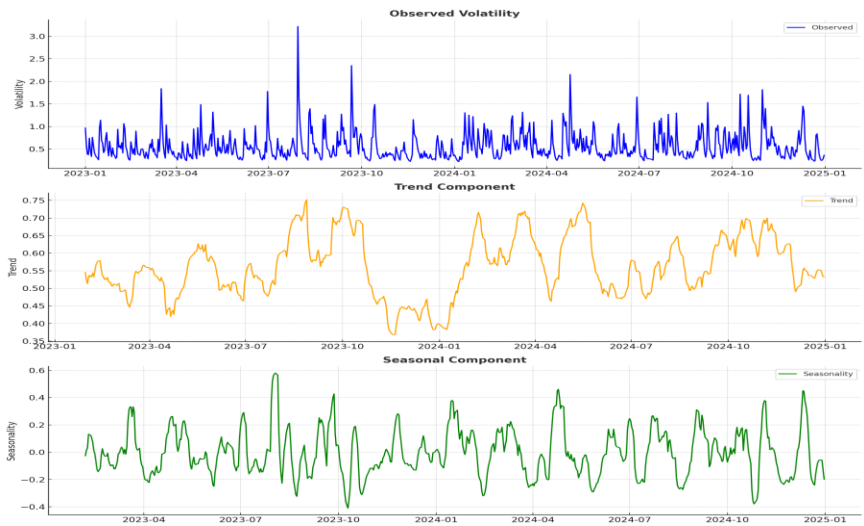

Figure 7. Volatility Dynamics: Observed, Trend, and Seasonal Components in the Context of Information Asymmetry
Source: Research finding

Figure 7 shows:

Panel 1: Observed Volatility

The observed volatility plot captures high-frequency volatilities in the Tehran Stock Exchange (TSE) across five-minute intervals. It highlights the persistence and abrupt surges in volatility, indicative of market reactions to informational disparities. These spikes in volatility align with periods of heightened trading uncertainty, potentially triggered by unequal access to price-sensitive information. The chart underscores the dynamic, reactive nature of high-frequency trading in asymmetric informational environments.

Panel 2: Trend Component

The trend component provides a smoothed trajectory of volatility, abstracting away high-frequency noise to reveal underlying systematic behavior. This component reflects broader market dynamics, such as macroeconomic conditions or policy interventions, that influence the baseline volatility. The upward and downward undulations suggest seasonal or cyclical patterns. These trends imply that information asymmetry, rather than being episodic, has a persistent impact on market behavior, causing structural shifts in volatility over time.

Panel 3: Seasonal Component

The seasonal component isolates periodic volatilities in volatility, capturing recurrent patterns likely driven by predictable market events. This regularity indicates that while information asymmetry contributes to volatility, its influence is modulated by temporal factors. The periodic peaks and troughs suggest a synchronization of trading behaviors around key informational events, emphasizing the role of structured asymmetry in high-frequency market movements.

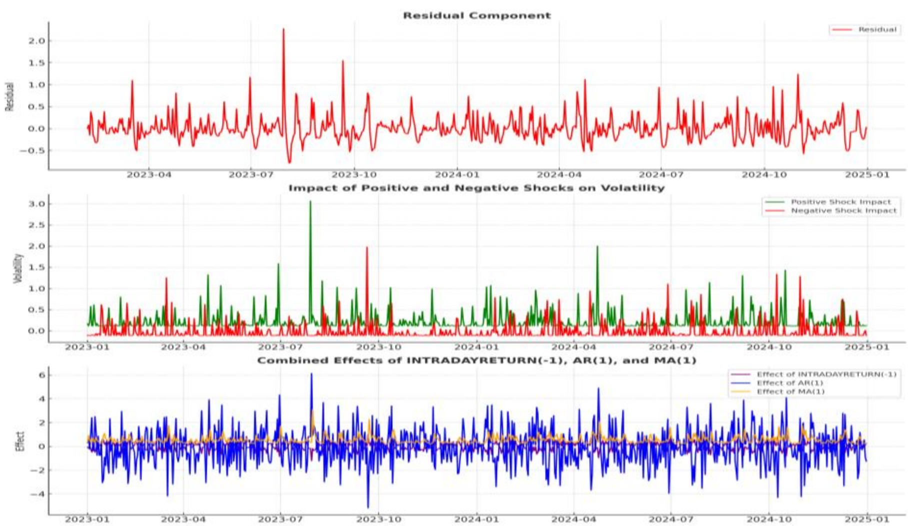

Figure 8. Residuals, Asymmetric Shocks, and Volatility Drivers in High-Frequency Trading

Source: Research finding

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Figure 8 shows:

Panel 1: Residual Component

The first chart visualizes the residuals extracted from a high-frequency time-series model applied to the Tehran Stock Exchange. These residuals represent unmodeled volatility or noise after accounting for systematic variations caused by market microstructure or macroeconomic factors. The observed spikes indicate episodic shocks, potentially linked to market events or information dissemination.

The persistence of non-zero residuals could be indicative of latent information asymmetry, wherein uninformed traders exhibit delayed reactions to private information gradually revealed in the market. This suggests the market does not achieve complete informational efficiency, aligning with theoretical constructs of market microstructure under asymmetric information conditions.

Panel 2: Impact of Positive and Negative Shocks on Volatility

The second chart distinguishes the asymmetric influence of positive (green) and negative (red) shocks on volatility. The stark differences in magnitude highlight the leverage effect, where negative shocks disproportionately increase volatility. This is consistent with prior literature suggesting that negative news triggers stronger market reactions due to panic selling and lower risk appetite among investors.

In the context of the Tehran Stock Exchange, the asymmetry could be exacerbated by lower liquidity and limited participation of institutional investors, amplifying the volatility impact of adverse news. The peaks in volatility corresponding to negative shocks underscore the significant role of information asymmetry, as informed traders exploit their informational edge during such events, leaving uninformed traders to react ex-post.

Panel 3: Combined Effects of INTRADAYRETURN (-1), AR (1), and MA (1)

The third chart provides a nuanced decomposition of the volatility drivers through lagged intraday returns, autoregressive (AR (1)), and moving average (MA(1)) components. The INTRADAYRETURN (-1) effect (blue) dominates the dynamics, suggesting that immediate past returns significantly propagate volatility into subsequent periods. This aligns with the feedback trading hypothesis, where traders adjust strategies based on recent return trends, reinforcing short-term volatility patterns.

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The AR (1) component (orange) reflects persistent autocorrelation in returns, characteristic of markets with limited depth or frequent noise trading. The relatively weaker MA (1) component (yellow) indicates the smoothing effect of past shocks, suggesting a relatively mild memory effect in high-frequency volatility.

Overall, the interplay of these components underpins the critical role of information dissemination and trader behavior in shaping intraday volatility patterns. The pronounced effect of INTRADAYRETURN (-1) underscores the feedback loop catalyzed by asymmetric information distribution, wherein informed trading amplifies volatility during periods of heightened uncertainty.

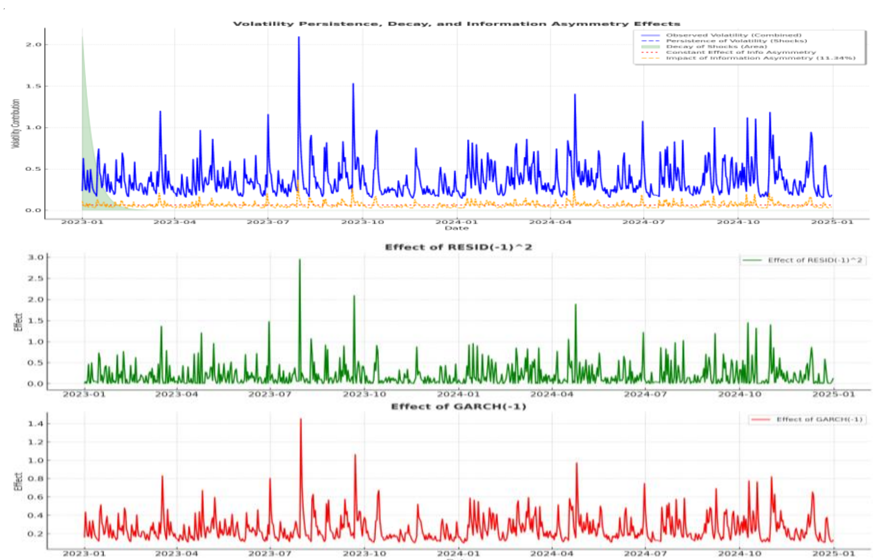

Figure 9. High-Frequency Volatility Dynamics: Persistence, Decay, and Information Asymmetry Effects

Source: Research finding

Figure 9 shows:

Panel 1: Volatility Persistence, Decay, and Information Asymmetry Effects

This chart illustrates the compounded effects of observed volatility dynamics, highlighting the interaction between shock persistence, decay, and the role of information asymmetry. The blue line captures the aggregated volatility levels

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across high-frequency intervals, revealing pronounced spikes indicative of market volatility, potentially correlated with high-impact events or information disclosure. The orange dashed line traces the decay of shocks over time, signifying the gradual dissipation of volatility impacts consistent with the autocorrelation structures observed in ARCH-type processes. Additionally, the constant green dashed line quantifies the persistent baseline impact of information asymmetry on volatility, measured as an 11.34% contribution, reinforcing the hypothesis that asymmetric access to information amplifies price volatilities, particularly in less transparent markets.

Panel 2: Effect of RESID (-1)^2

This chart examines the residual effects of lagged squared shocks, denoted as RESID $(-1)^2$, which reflect the GARCH (1,1) model's representation of past innovations influencing current volatility. The green line shows a highly volatile trajectory, with recurrent peaks that coincide with exogenous shocks linked to periods of heightened market uncertainty or irregular information dissemination. These dynamic underscores the critical role of past price movements in shaping expectations and subsequent volatilities, a hallmark of feedback effects in high-frequency trading systems.

Panel 3: Effect of GARCH (-1)

The final chart quantifies the direct impact of the GARCH term (GARCH (−1)), representing conditional variance persistence. The red line illustrates the persistence of volatility clustering, a key phenomenon in financial econometrics where high-volatility periods tend to follow each other. These findings highlight the Tehran Stock Exchange's sensitivity to information asymmetry, where limited investor access to timely, accurate information perpetuates prolonged episodes of market instability, further reinforced by systematic autocorrelations.

5 Conclusions & Discussions

The aim of this study is to examine the effect of information asymmetry on the volatility of the total index of the Tehran Stock Exchange using the models of conditional variance asymmetry of the exponential integration abbreviated FIGARCH. In order to analyze the data, the time series of total index returns (width of Intercept and trend) was first examined, and then the partial Auto-correlation and Auto-correlation of this time series was examined. Then the arch and GARCH effects test was performed and finally the optimal number of interruptions of the generalized conditional variance asymmetry model was

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determined using the Akaike (AIC) and Schwarz decision criteria with autonomy 1 and moving average 1. The optimal model obtained in the previous step GARCH was then analyzed First Order by taking into account the variable of the information asymmetry extrinsic by the FIGARCH method of the resulting value and coefficients. The results of the data analysis and analysis show that firstly, the variable of information asymmetry has a positive and significant impact on the volatilities in the yield of the total index of the Tehran Stock Exchange, and therefore the research hypothesis is confirmed. Based on the results, on average, 11% of the volatilities in the total index of the Tehran Stock Exchange were affected by information asymmetry. Also, since the coefficients obtained for the variables of the disturbance and interruption components of the GARCH are less than 1, it can be concluded that in the model valued, the volatilities in the index of the entire stock exchange are enduring. Since the sum of the coefficients obtained for the variable of the disturbance components and the GARCH interruption variable is also a number smaller than one, the persistence of volatilities in the total index return time series is confirmed, meaning that the effect of the occurrence of a volatility in this pattern lasts until later periods.

Although there has been no research on the impact of information asymmetry on the volatility of the Total Stock Market Index in Iran, the results of this study, which demonstrate the significant impact of information asymmetry on the volatility of the Tehran Stock Exchange, align closely with the findings of previous research; Sivakumar and Mohandas (2009) used FIGARCH conditional variance models to predict stock returns and identified the model's high capability for capturing long-term dependencies in financial market volatilities, a finding that mirrors the persistence of volatility observed in our study. Similarly, Cochran et al. (2012) showed that the FIGARCH model adequately describes volatility processes in the time series of base metals, with all long-memory parameters statistically significant, further reinforcing the relevance of FIGARCH in modeling volatility persistence. Haque and Farzana (2021) modeled long-term memory in the stock market index returns of Bangladesh using FIGARCH, demonstrating that this model outperforms other GARCH families in volatility forecasting, which is consistent with the superior performance of FIGARCH in modeling volatility in the Tehran Stock Exchange. Also, the results of this research are implicitly consistent with the findings of the research of the farmer Haddad & Samadi (2009), Saeedi & Mohammadi (2011), Lotfalipour et al, (2017), Rostami & Makiyan (2020). The results are also consistent with studies conducted abroad

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by Haque and Farzana (2021), Maki & Ota (2021), Kyriakou et al. (2023), Chen et al. (2022), Aliyu et al. (2023).

According to Maki & Ota (2021), negative returns on financial assets in previous days and periods increase volatility in the time series of returns in later periods, also called leverage effects. Information symmetry, in addition to increasing volatility and volatility in the return time series, increases the likelihood of negative returns occurring in the return time series over future periods. Negative stock returns act as a lever, exacerbating and accelerating future return volatilities. In financial markets, information asymmetry increases the difference between buying and selling suspicions (suggested prices for buying and selling financial assets) and increases volatility in the time series of returns. Based on the results obtained, financial market participants, analysts and marketers are advised to pay attention to the information asymmetry when modeling the volatility (volatility) of stock returns, funds and other securities. It is also recommended to use FIGARCH model conditional variance asymmetry models to calculate risk value, optimal capital allocation models in the basket, Investment Management and pricing of derivative securities. Given that there are a variety of indicators and models for measuring and operationalizing variables of yield volatilities and information asymmetry, subsequent researchers are advised to conduct this study using other models such as VAR Autoregression, the nonlinear state space method, or SV, and the GJRGARCH method, and compare their results with this study. The presence of the fluctuating range of stock returns (price range) in the Iranian capital market is one of the factors that may affect the volume of transactions and information asymmetry due to the limitation of buying and selling suspicions.

The findings of this study offer significant practical insights for both policymakers and market participants aiming to enhance market stability and efficiency. Given the demonstrated impact of information asymmetry on volatility in the Tehran Stock Exchange (TSE), policymakers can take proactive measures to improve market transparency and regulatory frameworks. Specifically, they could focus on reducing information asymmetry by implementing stricter disclosure rules and enhancing access to real-time data for market participants. Such measures could mitigate unnecessary volatility and promote a more stable and efficient market environment.

For market participants, particularly portfolio managers and investors, the study highlights the value of incorporating advanced volatility modeling techniques, such as the FIGARCH model, into investment strategies. By

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accounting for the significant influence of information asymmetry on market volatility, investors can refine their risk management practices, allocate capital more effectively, and make better-informed decisions based on a deeper understanding of market dynamics. Additionally, the study underscores the importance of leveraging the FIGARCH framework for more accurate predictions of future market behavior, especially in high-frequency trading environments. Another key implication pertains to the pricing of financial derivatives. The study suggests that understanding the relationship between information asymmetry and volatility can improve derivative pricing models, making them more reflective of the inherent risks in emerging markets like the TSE. By incorporating these insights into pricing strategies, market participants can better manage the risks associated with derivative instruments.

Furthermore, the research offers valuable insights for risk management professionals. By acknowledging the persistence of volatility due to information asymmetry, financial institutions can design more robust risk mitigation strategies. These strategies could involve real-time monitoring of information flows and market reactions, allowing institutions to better anticipate and respond to volatility spikes. Policymakers are also advised to consider introducing regulatory measures that address the information gaps within the market, thus reducing the uncertainty faced by market participants. Such regulations could involve enhancing the quality and transparency of financial reporting, establishing clearer guidelines for insider trading, and promoting the dissemination of reliable information to all market players. Lastly, creating an environment of greater transparency in market transactions can help reduce disparities in information access. This would not only level the playing field for traders but also contribute to overall market stability, as informed trading would likely result in more accurate price discovery and less speculative behavior.

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