IJAAF; Vol. 8, No. 4, Autumn 2024, Serial 29

Ferdowsi University of Mashhad

Iranian Journal of
Accounting, Auditing & Finance

Quarterly

RESEARCH ARTICLE

The Impact of Company Characteristics on Return Volatility in Sorted Portfolios: A Hybrid Asymmetric Conditional Variance Approach

Seyed Kazem Ebrahimi, Mahnaz Khorasani, Mina Saba*

Financial Engineering, Faculty of Economics, Management and Administrative Sciences, Semnan University, Semnan, Iran

How to cite this article:

Ebrahimi, S. K., Khorasani, M., & Saba, M. (2024). The Impact of Company Characteristics on Return Volatility in Sorted Portfolios: A Hybrid Asymmetric Conditional Variance Approach. *Iranian Journal of Accounting, Auditing and Finance*, *8*(4), 71-88. doi: 10.22067/ijaaf.2024.45105.1433
https://ijaaf.um.ac.ir/article_45105.html

ARTICLE INFO

Article History
Received: 2023-11-21
Accepted: 2024-03-06
Published online: 2024-10-25

Abstract

The primary objective of this study is to investigate how various stock portfolio strategies affect the volatility of returns among companies listed on the Tehran Stock Exchange (TSE). A systematic elimination method selected 185 companies from 2011 to 2022. The return volatility of these companies, along with the stability of fluctuations, was analyzed across 16 sorted portfolios based on three characteristics: size, book-to-market (B/M) ratio, and financial leverage. Additionally, considering the leveraged structure of companies' balance sheets, the extent of the leverage effect was examined in relation to the impact of positive and negative news on return fluctuations. The hybrid model ARMA(p, q)-GJR-GARCH(1, 1)-M was utilized to investigate this. The findings indicate that the volatility of returns and the stability of fluctuations within sorted portfolios vary across different groups. Furthermore, the influence of positive news on stock return volatility appears to be more pronounced in two specific portfolios: one consisting of large companies with a high B/M ratio and the other comprised of large companies with a low B/M ratio, compared to the impact of negative news. This disparity may be attributed to the dissemination of positive news within the market, wherein larger companies with low B/M ratios, due to their higher growth potential, and larger companies with high B/M ratios, due to their substantial capital and stable financial performance, have a greater impact on market expectations, thereby enhancing investor confidence.

Keywords:
Firm Value; Financial Leverage; Hybrid Asymmetric Conditional Variance; Return Volatility

https://doi.org/10.22067/ijaaf.2024.45105.1433

NUMBER OF REFERENCES
49

NUMBER OF FIGURES
0

NUMBER OF TABLES
7

Homepage: https://ijaaf.um.ac.ir
E-Issn: 2717-4131
P-Issn: 2588-6142

*Corresponding Author: Mina Saba
Email: saba6970@semnan.ac.ir
Tel: 09147993577
ORCID:

1. Introduction

The growing body of financial literature has increasingly focused on stock return volatility (Chen et al., 2010; Vo, 2015, 2016) due to its potential influence on firms' financial stability as well as the financial system (Vuong et al., 2024). Understanding and managing stock return volatility is crucial for firms, investors, and regulatory entities. Hence, surveying stock return volatility in stock markets is an attractive topic for economic researchers because it is relevant to stock investors' behaviors and corporate managers' decisions. High levels of volatility can lead to increased uncertainty, higher risk premiums demanded by investors, and potentially destabilize financial markets. Moreover, excessive volatility can hinder firms' ability to plan and execute long-term strategies (Kashyap, 2023). Generally, portfolio managers aim to design strategies that achieve higher returns than risk-adjusted returns. Many investors construct investment portfolios based on size, B/M, etc. (Otaify, 2020). Forming an investment portfolio is a paramount concern for managers and investors, who endeavor to construct the optimal investment portfolio to achieve maximum returns from the market (Nourahmadi and Sadeqi, 2023). Given that the fluctuation patterns in various assets differ, portfolios constructed based on distinct fundamental characteristics are anticipated to exhibit different returns and risk levels. Several studies have presented evidence highlighting the success of portfolio management strategies concerning factors such as size and the B/M.

Furthermore, empirical evidence indicates that negative shocks to financial time series lead to a more pronounced increase in the volatility of returns than positive shocks of equivalent magnitude. In the context of stock return, this asymmetry is termed the leverage effect, and one of the pivotal models for investigating these effects is the Glosten, Jagannathan, and Runkle (*GJR*) model. Additionally, many financial models assume that investors demand higher returns in exchange for taking on more risk. The GARCH-M model can be applied to explore this concept (Brooks, 2014). Thus, the main objective of the research is to employ a heterogeneous hybrid model of asymmetric conditional variance, ARMA (p, q)-GJR-GARCH (1, 1)-M, to assess the success rate of various portfolio management strategies based on three crucial characteristics: size, B/M and financial leverage. What distinguishes this study from others is that it investigates the impact of these variables in the form of sorted portfolios in the Iranian stock market, a facet not explored in previous research. Furthermore, the econometric model utilized in this research represents the first hybrid model used in this field. This advanced economic model, combining the capabilities of ARMA and GARCH, provides the best forecast for stock return fluctuations.

2. Research background

2.1 Theoretical Background

In the era of the global economy and dynamic financial markets, analyzing the factors influencing stock market fluctuations holds particular significance. One key influential factor in these fluctuations is the company's size and value (Asyik et al., 2023). One crucial aspect of analyzing the influence of company size on stock market fluctuations is the company's capacity to adapt to market changes. Research indicates that while large companies may possess greater financial and operational capabilities, they are more likely to experience heightened market volatility. Company size is recognized as an indicator of a company's significance and impact on the economy. Due to their broader economic effects, market movements, and business diversification, large companies may be significantly affected by market fluctuations (Rutkowska-Ziarko, 2015). On the other hand, small companies may experience market fluctuations due to their higher sensitivity to various factors. The company's size can influence several aspects of its financial performance and largely depends on market and industry conditions (Tahir et al., 2013).

Large companies, endowed with abundant resources, often can enhance the stability of their financial performance. This capability can lead to a reduction in return volatility. Moreover, increased transparency in the disclosure practices of large companies can boost investor confidence and mitigate return volatility (Ahmed and Hla, 2019). On the other hand, large companies may face challenges related to flexibility. This limited flexibility can result in these companies experiencing higher return volatility when confronted with market changes and economic conditions. In addition, the large size of a company may lead to a greater focus on diversification across various economic sectors. This diversification could have both positive and negative effects, as the impacts of different segments may balance each other, potentially reducing the overall return volatility of the company (Bhowmik and Wang, 2020). Overall, it can be said that the impact of company size on stock return volatility is dependent on various factors, including management, market conditions, and corporate policies. Generally, an increase in company size may sometimes reduce return volatility. In contrast, the opposite may be true in other cases, and an increase in size may result in higher return volatility. An increase in the firm's market value is related to a rise in volatility (Shin and Stulz, 2000). High growth could cushion the negative effects of stock return volatility on firm value. If a company is experiencing significant growth, investors might be more willing to accept higher levels of stock return volatility because they anticipate future returns from the company's expansion. In such cases, high growth modifies by reducing the adverse impact of stock volatility on firm value. Conversely, low growth could amplify the detrimental effects of stock return volatility on firm value. When a company is experiencing limited growth prospects, investors might perceive high stock volatility as an uncertainty indicator. This situation could lead to a greater decline in firm value (Vuong and Nguyen, 2024).

Furthermore, the price-to-book ratio is identified as a significant indicator in determining the financial health of companies and can directly influence stock market fluctuations. The price-to-book ratio of the market value is a fundamental variable in the analysis of stock market fluctuations. This ratio can reflect the relative value of a company compared to the total market value. A high P/B ratio may indicate overvaluation or misinformation about the company's equity value, potentially contributing to market fluctuations (Pontiff and Schall, 1998). The impact of the book-to-market value ratio on stock return volatility is dependent on various factors. The P/B ratio typically plays a role in determining systematic risk. For example, an increase in the P/B ratio may indicate investors' expectations of improved profitability for the company, leading to increased stock sensitivity to market changes. In some cases, an increase in the P/B ratio may indicate a higher increase in market value compared to book value, possibly signaling a mismatch between market and true company value. This could result in increased stock return volatility. Additionally, an increase in the P/B ratio may be driven by an increase in market value surpassing the increase in book value, indicating a potential mismatch between market and true company value and consequently increasing stock return volatility (Nugroho, 2020). The effects of the P/B ratio on stock return volatility also depend on economic and industry factors. In some industries, this ratio is considered a more reliable indicator of book value, while in others, due to industry-specific characteristics, this relationship may be less significant. For a precise analysis of the effects of the P/B ratio on stock return volatility, an examination of the company's specific conditions, industry, and economic conditions is required (Park, 2019).

Corporate financial leverage is considered one of the most significant factors influencing stock market fluctuations. According to the Trade-off theory (TOT), firms with higher volatility may face a greater risk of financial distress; therefore, they are cautious about using debt ratios in their capital structure (Modigliani and Miller, 1958). Stock return volatility is a concern for stakeholders, particularly when it can exert significant pressure on the overall economy. Moreover, economic, political, or financial shocks are more pronounced in emerging equity markets. The volatility of cash flows generated by a firm's existing assets and potential growth options affects its market value. This volatility increases external financing costs (Ahmed and Hla, 2019), impeding managers from utilizing debt due to heightened bankruptcy risks. Companies benefit from tax shields by employing debt but incur financial distress costs (Ghasemzadeh et al., 2021). Listed firms can respond to equity volatility by reducing their debts to mitigate bankruptcy risk (Krause and Tse, 2016).

When a company finances its capital through debt, its sensitivity to economic and financial changes increases. Companies with higher debt levels may face more pronounced stock return fluctuations in different economic conditions (Nukala and Prasada Rao, 2021). Companies utilizing financial leverage in their capital structure may experience the leverage effect in response to positive or negative news (Al-Slehat et al., 2020). According to the leverage effect model, shocks are divided into positive (good news) and negative (bad news), with the same absolute magnitude potentially having different effects on conditional volatility. The theoretical argument suggests that the debt portion of the firm's financial structure increases as stock prices decrease. Consequently, shareholders assume higher risks and expect future stock return fluctuations to increase. Many empirical studies, such as Christie (1982), Nelson (1991), Engle and Ng (1993), Friedmann and Sanddorf-Köhle (2002), have demonstrated that negative shocks (bad news) have a greater impact on stock return fluctuations compared to positive shocks (good news) of the same magnitude. As a result, market fluctuations in stock markets are asymmetric (Mehrara and Abdoli, 2006).

In this research, considering that the complex relationships among these variables affecting stock return volatility may change over time, simultaneous examination of the impact of these variables in constructed portfolios enables better analysis of market dynamics and changes. Therefore, using the hybrid model proposed in this research, the impact of various stock portfolio strategies based on company size, firm value, and financial leverage on the volatility of returns and the degree of stability in fluctuations is examined. In addition, given the use of financial leverage in the capital structure of companies, the leverage effect is examined in the context of the impact of good and bad news on the volatility of stock returns in portfolios.

2.2 Empirical Background

Lam (2002) investigated the relationship between stock returns and beta, size, B/M, leverage, and price-to-earnings ratio (P/E) in the Hong Kong stock market using the Fama and French model from 1980 to 1997. The results indicated that the beta coefficient could not explain the average returns of the examined companies. However, size, B/M, P/E ratio, and company leverage could capture cross-sectional variations in monthly average returns over the period. Additionally, Ehrmann and Fratzscher (2004) argue that low financially leveraged firms have the largest effect on monetary policy, perhaps because they currently face financial constraints that prevent them from borrowing more debt. Moreover, Li et al. (2009) estimate the volatility properties of value, growth, and HML portfolios in the context of the GARCH model and convey interesting results. Firstly, the volatility of the value portfolio is more (less) sensitive to recent (older) information than the growth portfolio. Secondly, the volatilities of both the value and the HML portfolios are indifferent to good or bad news. Still, the volatility of the growth portfolio increases after the announcement of bad news. Finally, using the GJR-GARCH (1,1)- M model, the authors document a positive, significant relation between the excess return of the value portfolio and the time-varying volatility. In contrast, the excess return of the growth portfolio is negatively related to volatility. Therefore, the expected return of the value premium (HML portfolio) is positively associated with its time-varying volatility. Consequently, the authors argue that the return on the value portfolio is more sensitive to its volatility than the growth portfolio.

Cenesizoglu et al. (2011) demonstrated that the returns of different portfolios respond to different news and exhibit different reactions to similar news. The results show that returns on various portfolios respond differently to different news and react diversely to the same news. Furthermore, the response of portfolios to macroeconomic news also varies across the business cycle. Large and growth firms exhibit distinct reactions to employment news at daily and monthly frequencies compared to small and value firms during expansions but not recessions. Furthermore, Kontonikas et al. (2013) indicated that value stocks, small-cap stocks, and past loser stocks are more exposed to monetary policy shocks than growth stocks, large-cap stocks, and past winner stocks. Moreover, Vithessonthi and Tongurai (2015) showed that the extent of the impact of financial leverage on operational performance is contingent upon the firm's size. While the regression results of combined data suggested a negative effect of financial leverage on the performance of companies, cross-sectional regression results indicated a positive effect of leverage on performance for small companies and a negative effect for large companies. Additionally, Ibhagui and Olokoyo (2018) examined the empirical relationship between financial leverage and firm performance using the Hansen threshold regression and considering firm size as the threshold variable. They sought to answer whether there is an optimal firm size where the relationship between leverage and firm performance is not negative. The results indicated that the negative impact of leverage on firm performance is significant for small companies and diminishes with company growth. Ultimately, when the firm size exceeds its estimated threshold level, this impact disappears, and the obtained result holds irrespective of the debt ratios employed.

Otaify (2020), using the AR(1)-GJR-GARCH(1,1)-M model, examined the volatility characteristics of portfolios sorted based on three features: firm size, B/M, and financial leverage in the Egyptian stock market. The findings indicate that sorted portfolios with these characteristics exhibit various degrees of clustering in terms of volatility and stability. Additionally, the results suggest that bad news has a greater impact on these portfolios' volatility than good news, regardless of their size. Furthermore, Ramezani Sharif Abadi et al. (2022) investigated the impact of combining size, value, and idiosyncratic risk anomalies with tail risk on stock excess returns. Using two tail risk measures, Aggregate Tail Risk and Hybrid Tail Covariance Risk, they applied the Five-Factor Fama and French model (2015) to test their hypotheses. Their findings revealed that combining size or value with tail risk decreased excess returns, whereas combining idiosyncratic risk with tail risk resulted in higher excess returns. Additionally, Vuong and Nguyen (2024) estimated the relationship between firm value, stock return volatility, and growth opportunity in the framework of the GGM model and presented interesting results. Firstly, they shed light on the effect of stock return volatility on corporate value in the Vietnamese equity market after experiencing the primitive stage. A deep understanding of this link becomes necessary for an opening and young equity market in the ASEAN area. Secondly, their research shows that Vietnamese-listed firms with higher stock return volatility have a lower value. This finding hints at Vietnamese corporate managers needing to enact controlling policies for stock return volatility, thereby improving corporate value. Thirdly, further investigation shows that a positive nexus between stock return volatility and firm value is more prominent in growth companies and technology firms. Put differently, a negative association between firm value and stock return volatility is less pronounced in tech and growth enterprises.

Recent studies have generally overlooked the effect of stock portfolio strategies in the Iran stock market, particularly those based on size, B/M, and financial leverage. To address this gap, this study proposes employing a hybrid model approach. Additionally, this research introduces the use of the hybrid econometric model ARMA (p, q)-GJR-GARCH (1,1)-M, which allows for a simultaneous examination of firm characteristics' influence on stock return volatility, fluctuations' stability, and the impact of shocks. This innovative approach offers a significant improvement in understanding the behavior of financial asset markets, considering complexities and temporal variations, thus providing a more comprehensive analysis.

3. Data and methodology

3.1 Sample selection and data sources

Our sample covers all companies listed on the TSE from 2011 to 2022. All company data was extracted from Rahvard Navin software. The variables include monthly total returns, size, B/M, and financial leverage. Because volatility analysis requires active stocks, the testable stocks must meet the following criteria:

1. They should have been traded annually for at least 80% of all trading days.
2. Their financial statements should conclude at the end of December each year.
3. Exclude stocks belonging to financial companies and institutions.
4. Exclude stocks with a negative book value of equity.

Based on the mentioned criteria, 185 companies have been selected as samples for this research.

3.2 Variables

Size: The size is measured as the logarithm of the firm’s total assets (Vuong and Nguyen, 2024).

Book Value to Market Value (B/M): The B/M ratio is calculated by dividing the book value of equity at the end of the financial year by the market value of equity at the end of June (Fama and French, 2018)

Financial Leverage: Financial leverage is the ratio of total long-term debt to total stockholders' equity. In order to prevent the look-ahead bias, this study followed previous studies (e.g., Fama and French, 2015, 2018; Otaify, 2020) and utilized the 6-month lagged values of financial leverage and book value to ensure that financial statements were accessible to investors in the market while constructing portfolios.

Monthly Stock Return: Monthly stock return is defined as the difference between the price of each share at the end of two consecutive months (adjusted for dividends and capital increases), divided by the price per share at the end of the previous month (Pätäri et al., 2023).

3.3 Construction of the characteristics-sorted portfolios

Following the literature, we utilized 50% -50% breakpoints to sort stocks based on their size into big (top 50%) and small (bottom 50%) portfolios. Additionally, we applied breakpoints (30-40-30) to sort stocks based on their B/M into value (top 30%), medium (middle 40%), and growth (bottom 30%) portfolios. Subsequently, we employed 50%-50% breakpoints to sort stocks based on their financial leverage into high (top 50%) and low (bottom 50%) financial leverage portfolios. These portfolios are denoted by two letters. The first letter represents the Size group, small (S) or big (B); the second letter represents the B/M group, indicating growth stock (G), Medium value stock (M), or value stock (V); and the third letter indicates the financial leverage group, high (H) or low (L) financial leverage. These seven portfolios jointly constructed 16 portfolios as shown in Table 1.

3.4 Research model

In this study, we follow Otaify (2020) and apply the ARMA (p, q)-GJR-GARCH (1,1)-M model to examine the impact of various stock portfolio allocation strategies on stock return volatility. This section begins with an explanation of the ARMA-GARCH model methodology, followed by a description of the hybrid model ARMA (p, q)-GJR-GARCH (1,1)-M.

Table 1. Characteristics-Sorted Portfolios

Portfolio	Abbreviation symbol
Big Size, Low Leverage	BL
Small Size, Low Leverage	SL
Small Size, High Leverage	SH
Big Size, High Leverage	BH
Small Size, Growth Stock	SG
Small Size, Medium Value Stock	SM
Small Size, Value Stock	SV
Big Size, Growth Stock	BG
Big Size, Medium Value Stock	BM
Big Size, Value Stock	BV
Low Leverage, Growth Stock	LG
Low Leverage, Medium Value Stock	LM
Low Leverage, Value Stock	LV
High Leverage, Growth Stock	HG
High Leverage, Medium Value Stock	HM
High Leverage, Value Stock	HV

3.4.1 ARMA-GARCH Model

Financial institutions commonly use the ARMA-GARCH predictive model to model the returns and volatility of financial assets. The first part of these models, the Autoregressive Moving Average (ARMA) model, is one of the most common models for modeling the returns of financial assets. Introduced by Box et al. (1976), this model was designed to forecast time series data of a single variable. This model is formed by combining an Autoregressive (AR) process and a Moving Average (MA) process. The second part of the ARMA-GARCH model is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, specifically designed for modeling the volatility of financial assets. The GARCH model consists of two equations: the conditional mean equation and the conditional variance equation. By representing the conditional mean equation as an ARMA process, we can combine the concepts of ARMA and GARCH to obtain an ARMA-GARCH model suitable for predicting returns. To better understand the ARMA-GARCH model, it is essential to differentiate between unconditional and conditional mean and variance. The unconditional mean and variance are simply the mean and variance of the return distribution considered over the entire period, assumed to be constant. It can be regarded as the long-term mean and variance for that period. On the other hand, conditional mean and conditional variance will vary at each point in time. Conditional mean and conditional variance depend on the past behavior of returns up to that time, and the conditional mean equation specifies the behavior of returns (Grachev, 2017).

3.4.2 Conditional Mean Equation

The conditional mean equation in a GARCH model can take various forms, and in this research, it is assumed that the return series follows an Autoregressive Moving Average (ARMA) model. The ARMA is defined as follows (Liu and Shao, 2016):

$$r_{i,t} = c_i + \sum_{j=1}^{p} k_{i,j}\, r_{i,t-j} + \sum_{j=1}^{q} \mu_{i,j}\, \varepsilon_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

Where:

- c_i the constant term
- $r_{i,t}$ is the observed realized return at the time
- k_{ij} represents the autoregressive terms
- $\varepsilon_{i,t-1}$ is the realized error at the time t

- $\mu_{i,j}$ is the moving average coefficient
- $\varepsilon_{i,t}$ is the white noise

3.4.3 Conditional Variance Equation

In 1982, Engle proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model as a method for examining fluctuations in a variable. The idea behind the ARCH approach is that the current period's variable volatility depends on information from previous periods. In other words, considering data from the previous period will make the volatility estimation more accurate (Mirzaei et al., 2019). This model assumes that the random term has a mean of zero and is serially uncorrelated, but its variance is conditional on its past information. In other words, the Autoregressive Conditional Heteroskedasticity (ARCH) model can explain the conditional variance trend using its past information (Manzoor and Yadi-Poor, 2016). The conditional variance equation presented by Engle (1982) is defined as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \qquad (2)$$

In the above equation σ_t^2 represents the conditional variance for the current period (t), where α_0 and α_1 are constant coefficients and ε_{t-1}^2 is the squared error term at the previous period (t-1). In this equation, to ensure the positivity of the variance, it is considered that $\alpha_0 \geq 0$, and for stability, α_1 should be between 0 and 1 ($0 \leq \alpha_1 \leq 1$). For higher-order interruptions, the ARCH equation will be as follows.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \cdots + \alpha_P \varepsilon_{t-P}^2 \qquad (3)$$

The above relation represents an ARCH model of order p (Mirzaei et al., 2019). According to what has been observed in empirical studies, the order of ARCH is often large, leading to an increase in the model parameters. To address this issue, Bollerslev (1986) proposed the following model:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^2 \qquad (4)$$

In the above equation, to ensure the positivity of the variances, α_i and β_j are assumed to be positive. This model is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model (p, q), essentially an extended version of the ARCH model. If q equals zero in this model, it will be the same as the ARCH (p) model (Zabol and Abounoori, 2020).

3.4.4 The ARMA (p, q)-GJR-GARCH (1,1)-M model

The GJR-GARCH model is one of the conditional heteroskedasticity models within the GARCH family, introduced by Glosten et al. (1993). The primary advantage of the GJR-GARCH model lies in its ability to model leverage effects, such as good and bad shocks in financial markets. The GJR-GARCH model includes a single extra leverage parameter in the conditional variance equation. Using an indicator function, this extra parameter is formulated to augment the asymmetric response only by negative market shocks. Furthermore, the conditional mean equation and relation (1) are now enhanced by including the conditional volatility term to model volatility feedback. Collectively, we obtain the ARMA (p, q)-GJR-GARCH (1,1)-M model, represented by the following expressions (Rønold and Hausken, 2018):

$$r_{i,t} = c_{i,s,t} + \sum_{j=1}^{P} k_{i,s,j} r_{i,t-j} + \sum_{j=1}^{q} \mu_{i,s,j} \epsilon_{i,s,t-j} + \eta_{i,s,j} \sigma_{i,t} + \epsilon_{i,s,t} \qquad (5)$$

$$\sigma_{i,t}^2 = \omega_{i,s,t} + \alpha_{i,s,t}\epsilon_{i,s,t-1}^2 + \lambda 1_{\{\epsilon_{i,s,t-1}<0\}}\epsilon_{i,s,t-1}^2 + \beta_{i,s,t}\sigma_{i,t-1}^2 \quad (6)$$

4. Empirical analysis and interpretation of the results

Given that the random trend of time series variables in econometrics may lead to misinterpretation or pose challenges in selecting the type of estimation and validating results, the first step in addressing this issue is to examine whether or not there is a unit root in the time series. This step is of particular importance. In this regard, two generalized Dickey-Fuller tests and the Phillips-Perron test were employed to examine the existence or absence of a unit root in the variables' trends. Based on the results of both unit root tests in Table 2, the probability values for all research variables within their sorted portfolios are less than one percent. Therefore, all variables are stationary at the level.

Table 2. Stationary Test of Formed Portfolios

Variables	Dickey-Fuller Test	Phillips- Perron Test
BL	-43.011	-43.751
	(0.000)	(0.000)
SL	-45.391	-45.767
	(0.000)	(0.000)
SH	-46.439	-47.123
	(0.000)	(0.000)
BH	-40.170	-41.124
	(0.000)	(0.000)
SG	-34.548	-35.248
	(0.000)	(0.000)
SM	-37.937	-38.570
	(0.000)	(0.000)
SV	-39.329	-39.448
	(0.000)	(0.000)
BG	-35.860	-36.559
	(0.000)	(0.000)
BM	-32.656	-33.116
	(0.000)	(0.000)
BV	-33.395	-33.945
	(0.000)	(0.000)
LG	-40.654	-41.407
	(0.000)	(0.000)
LM	-33.224	-33.768
	(0.000)	(0.000)
LV	-34.046	-34.127
	(0.000)	(0.000)
HG	-29.282	-29.877
	(0.000)	(0.000)
HM	-37.740	-38.440
	(0.000)	(0.000)
HV	-38.829	-39.371
	(0.000)	(0.000)

Now, after checking the absence of unit root to ensure the results of ARMA (p, q)-GJR-GARCH (1, 1)-M models, it is necessary to check the presence or absence of homogeneity of variance in the portfolios. The ARCH test has been employed for this purpose, and the results of this test are presented in Table 3.

Table 3. ARCH Test

Variables	ARCH Test	P-Value
BL	41.368	0.000
SL	0.000	0.987
SH	34.769	0.000
BH	69.457	0.000
SG	5.917	0.015
SM	18.804	0.000
SV	0.000	0.992
BG	27.024	0.000
BM	40.259	0.000
BV	49.604	0.000
LG	18.370	0.000
LM	5.083	0.024
LV	0.000	0.984
HG	11.848	0.000
HM	58.186	0.000
HV	20.578	0.000

Based on the results obtained from the ARCH test, the null hypothesis of homoskedasticity is not rejected for three portfolios, SL, SV, and LV, out of the 16 portfolios studied. Therefore, the ARMA (p, q)-GJR-GARCH (1, 1)-M model does not apply to these three portfolios, and the model estimation is carried out for the remaining 13 portfolios. These 13 portfolios are divided into three sections: portfolios sorted by size and financial leverage, portfolios sorted by size and B/M, and portfolios sorted by B/M and financial leverage. This division is done to achieve better result differentiation.

Table 4 presents the results of the ARMA (p, q)-GJR-GARCH (1,1)-M models based on size and financial leverage. According to the results in Table 4, it can be stated that the constant term (C), the GARCH coefficient (β), and the mean coefficient in the estimated model (SQRT) for the portfolio of small-sized and high-leverage companies (SH) are significantly higher than those for big-sized and low-leverage companies (BL) and big-sized and high-leverage companies (BH). These findings indicate that the returns, variance, and average volatility of small-sized and high-leverage companies, compared to other portfolios in Table 4, have the highest level of volatility. Moreover, the stability of each portfolio can be obtained by calculating the sum of the two ARCH and GARCH coefficients ($\alpha + \beta$). In this regard, the results show that the stability of the portfolio of big-sized and high-leverage companies (BH) is higher than that of the other portfolios. This implies that the shocks entering these companies will impact these portfolios in the long term. Another significant result emphasized in the analysis of these models is the leverage effect coefficient (η).

The positive or negative nature of this coefficient has different interpretations. If the leverage effect coefficient is positive, it indicates a greater impact of positive news compared to negative news on the variable trend and vice versa. In this regard, in the estimated model for all three portfolios, the leverage effect coefficient is negative and significant, indicating that negative news has a greater impact than positive news on the trend of these portfolios. Additionally, the estimated ARMA coefficients in the models are also statistically significant.

Table 4. Estimation Results for Portfolios Sorted by Size and Financial Leverage

Variables	**Model**	***SQRT***	**AR**	**MA**	**C**	$\boldsymbol{\alpha}$	$\boldsymbol{\eta}$	$\boldsymbol{\beta}$
BL	ARMA(1,2)-GJR-GARCH(1,1)-M	0.274 (0.038)	AR(1) -0.976 (0.000)	MA(1) 1.176 (0.000) MA(2) 0.188 (0.000)	16.611 (0.000)	0.299 (0.000)	-0.166 (0.000)	0.518 (0.000)
SH	ARMA(4,4)-GJR-GARCH(1,1)-M	0.537 (0.001)	AR(1) -0.002 (0.973) AR(2) 0.016 (0.858) AR(3) -0.291 (0.000) AR(4) -0.777 (0.000)	MA(1) 0.062 (0.464) MA(2) -0.053 (0.517) MA(3) 0.308 (0.000) MA(4) 0.809 (0.000)	83.449 (0.000)	0.196 (0.000)	-0.175 (0.000)	0.642 (0.000)
BH	ARMA(3,4)-GJR-GARCH(1,1)-M	0.319 (0.000)	AR(1) 0.488 (0.000) AR(2) 0.124 (0.493) AR(3) -0.816 (0.000)	MA(1) -0.354 (0.011) MA(2) -0.193 (0.208) MA(3) 0.825 (0.000) MA(4) 0.083 (0.024)	44.470 (0.000)	0.480 (0.000)	-0.344 (0.000)	0.513 (0.000)

In Table 5, portfolios are sorted based on size and B/M. The results of this table indicate that in two portfolios, the ones consisting of big-sized companies with high B/M (BV) and the portfolio of big-sized companies with low B/M (BG), the obtained GARCH leverage coefficients (η) are positive and significant, contrary to the sign direction of other portfolios. The positivity of the GARCH leverage effects suggests that positive shocks (good news) cause more volatility in these portfolios than negative shocks (bad news). In contrast, for other portfolios, the leverage effect of negative shocks (news) on the volatility of portfolio returns is more pronounced than positive shocks. Furthermore, in line with theoretical expectations, the results show that the stability (α + β) of the BV portfolio (big size and big value) is higher than other portfolios. Therefore, it is evident that as the company's value increases, it undoubtedly possesses a higher level of assets. Moreover, a bigger size will contribute to better stability in crisis conditions than other investment companies. Additionally, among the portfolios, the mean coefficient in the estimated model (SQRT) for the SG portfolio (small size and low B/M) is higher than that of other portfolios, indicating that the average volatility change in this type of portfolio from companies is higher. Also, the high intercept coefficient in the SG portfolio suggests a higher return for this type of company than other companies. The estimated ARMA coefficients in the models are also statistically significant.

Table 5. Estimation Results for Portfolios Sorted by Size and B/M

Variables	Model	$SQRT$	AR	MA	C	α	η	β
SG	ARMA(1,1)-GJR-GARCH(1,1)-M	1.678 (0.035)	AR(1) 0.822 (0.000)	MA(1) -0.776 (0.000)	291.773 (0.000)	0.026 (0.000)	-0.124 (0.000)	0.048 (0.000)
SM	ARMA(1,2)-GJR-GARCH(1,1)-M	-0.302 (0.325)	AR(1) 0.802 (0.000)	MA(1) -0.562 (0.000) MA(2) -0.092 (0.008)	115.539 (0.000)	0.216 (0.000)	-0.353 (0.000)	0.574 (0.000)
BG	ARMA(3,1)-GJR-GARCH(1,1)-M	1.538 (0.000)	AR(1) 0.563 (0.008) AR(2) -0.073 (0.170) AR(3) 0.006 (0.008)	MA(1) -0.336 (0.116)	31.929 (0.000)	0.045 (0.000)	0.062 (0.000)	0.036 (0.000)
BM	ARMA(3,3)-GJR-GARCH(1,1)-M	-0.064 (0.744)	AR(1) 1.419 (0.000) AR(2) -0.060 (0.289) AR(3) -0.370 (0.000)	MA(1) -1.215 (0.000) MA(2) -0.213 (0.000) MA(3) 0.436 (0.000)	98.107 (0.000)	0.410 (0.000)	-0.314 (0.000)	0.313 (0.000)
BV	ARMA(3,3)-GJR-GARCH(1,1)-M	0.444 (0.000)	AR(1) 1.535 (0.000)	MA(1) -1.396 (0.000)	6.649 (0.000)	0.401 (0.000)	0.063 (0.000)	0.545 (0.000)

In Table 6, companies' portfolios are sorted based on financial leverage and B/M to better distinguish portfolio results. According to the results of this table, the return rate (C) in the portfolio of companies with low financial leverage and medium value (LM) is the highest compared to other portfolios. Additionally, the stability of companies with high financial leverage and medium value (HM) is better than that of other portfolios, especially in critical and unfavourable financial conditions. This may be because companies with high leverage, presumably, can better cope with financial challenges and experience greater stability by having a strong ability to finance. Furthermore, the results indicate that, in line with theoretical expectations, the mean coefficient in the estimated model (SQRT) for companies with high financial leverage and B/M (HV) is higher than other portfolios. This is because, obviously, the higher a company's financial leverage, the greater the likelihood of discontinuous return changes. However, a noteworthy point in the classification results of this group is that the GARCH leverage coefficient for the return of the entire group of these companies is negative and significant. This suggests that negative news effects outweigh positive news effects, leading to changes in the trend of this group of portfolios. Additionally, the estimated coefficients of the ARMA models are also significantly meaningful.

Now, one of the ways to ensure the adequacy of the fitted models is to perform goodness-of-fit tests. In this regard, the fitted models for portfolios with variance homogeneity should exhibit no variance after the model estimation. Based on this, the ARCH test has been conducted to investigate this matter, and the results indicate that this test's null hypothesis has not been rejected for all 13 portfolios. The results of this test are presented in Table 7 based on the sorted portfolios. Therefore, the fitted models do not exhibit variance homogeneity; thus, the model estimation results can be relied upon.

Table 6. Estimation Results for Portfolios Sorted by **Financial Leverage and B/M**

Variables	Model	$SQRT$	AR	MA	C	α	η	β
LG	ARMA (1,2)-GJR-GARCH(1,1)-M	0.345 (0.041)	AR (1) -0.768 (0.004)	MA (1) 0.986 (0.000) MA(2) 0.153 (0.068)	78.647 (0.000)	0.277 (0.000)	-0.230 (0.000)	0.556 (0.000)
LM	ARMA(1,1)-GJR-GARCH(1,1)-M	-0.728 (0.002)	AR (1) 0.329 (0.000)	MA (1) -0.011 (0.874)	188.479 (0.000)	0.290 (0.000)	-0.431 (0.000)	0.224 (0.000)
HG	ARMA(3,3)-GJR-GARCH(1,1)-M	-1.775 (0.000)	AR (1) -0.906 (0.000) AR (2) 0.017 (0.876) AR (3) 0.603 (0.000)	MA (1) 1.307 (0.000) MA (2) 0.582 (0.000) MA (3) -0.255 (0.001)	182.853 (0.000)	0.207 (0.000)	-0.330 (0.000)	0.300 (0.000)
HM	ARMA(1,1)-GJR-GARCH(1,1)-M	0.397 (0.005)	AR (1) -0.398 (0.001)	MA (1) 0.563 (0.000)	59.810 (0.000)	0.298 (0.000)	-0.264 (0.000)	0.621 (0.000)
HV	ARMA(1,2)-GJR-GARCH(1,1)-M	0.536 (0.000)	AR (1) 1.062 (0.000)	MA (1) -0.980 (0.000)	77.215 (0.000)	0.292 (0.000)	-0.129 (0.000)	0.570 (0.000)

Table 7. ARCH Test

Variables	ARCH Test	P-Value
BL	0.898	0.334
SH	0.053	0.817
BH	0.500	0.479
SG	1.974	0.160
SM	0.510	0.820
BG	0.339	0.560
BM	0.914	0.339
BV	0.254	0.613
LG	0.810	0.775
LM	0.370	0.542
HG	0.766	0.381
HM	0.021	0.883
HV	1.153	0.282

5. Conclusion

In the context of the expanding significance of financial markets, any fluctuations in these markets have considerable impacts on the economy. Given the role of a diversified and appropriate portfolio in risk reduction and considering investors' uncertainty about the future, taking measures to mitigate risk becomes crucial. Formulating a diverse portfolio can significantly decrease overall risk. While numerous strategies for selecting portfolios with desirable returns and minimal risk have been explored in existing research, the efficacy of these selections depends on diverse factors and parameters influencing the risk and return of the portfolio. This study examines the impact of different equity portfolio strategies on stock return volatility and the stability of fluctuations from three perspectives: financial leverage, company value, and size. This investigation employs a hybrid model, ARMA (p, q)-GJR-GARCH (1, 1)-M. Furthermore, given the leverage structure of companies' balance sheets, the impact of leverage on the volatility of stock returns in the context of both positive and negative news has been investigated. To this end, a systematic elimination method was employed, and 185 active companies listed on the TSE from 2011 to 2022 were selected:

1. Classification Based on Size and Financial Leverage: When ranking companies in portfolios based on size and financial leverage, smaller-sized companies with bigger financial leverage exhibit higher returns, variance, and average volatility compared to other portfolios. Moreover, greater stability is observed in portfolios with big size and leverage, and negative news has a more significant impact on the trend of these portfolios compared to positive news.

2. Classification Based on Size and B/M: In portfolios categorized by size and B/M, positive news has a greater effect than negative news in portfolios with big size and low B/M, as well as big size and high B/M. Conversely, for other portfolios, the impact of negative news is greater than positive news. The stability of portfolios with big size and big value is also higher than other portfolios. The mean coefficient in the estimated model (SQRT) indicates that the average changes in portfolios with small size and low B/M are greater than those of other companies.

3. Classification Based on Financial Leverage and B/M: Regarding portfolios categorized by financial leverage and B/M, portfolios with low leverage and medium B/M have the highest returns among other classifications. Companies with big leverage and medium value demonstrate greater stability than other portfolios, and the mean coefficient in the estimated model (SQRT) in portfolios with high leverage and high B/M is higher than in other portfolios. However, a crucial result in this classification is that the effects of negative news, compared to positive news, cause more changes in the trend of all companies in this portfolio group.

Based on the findings of the research and utilizing the hybrid ARMA (p, q)-GJR-GARCH (1, 1)-M model, it is recommended that investors and market participants incorporate intelligent strategies based on this model into their decision-making processes. This hybrid model, combining ARMA and GARCH components, provides potential capability for predicting market fluctuations and optimizing risk management. Employing this model as a powerful analytical tool enhances the guidance of investors in their decision-making processes, contributing to accuracy and efficiency in predicting and managing market fluctuations. Investors are advised to diversify their investment portfolios using broad and diverse strategies to optimize investment performance. Selecting balanced strategies, considering factors such as financial leverage, B/M, and size, is crucial. Additionally, developing a news management system to reduce the impact of market changes and price fluctuations can lead to sustainable improvement in investment performance. It is recommended that the stability of companies be given sufficient importance in investment selection so that factors affecting yield fluctuations are properly considered.

Based on the current research findings, it is recommended that more advanced models such as hybrid models like ARIMA-ANN, GARCH-ANN, VAR-MLP, LSTM-SVR, LSTM -XGBOOST and ARIMA-SVR be employed in the analysis of financial markets in future studies. The application of neural network models, considering their deep learning capabilities and more complex interaction with information, can contribute to improving prediction accuracy and interpreting market complexities. Additionally, advancing sophisticated mathematical models and systemic analysis, taking into account various factors and their interactive effects, can aid in interpreting study results and enhance the accuracy of the analysis. Furthermore, improving analyses by considering new variables, such as economic indicators or other market variables, and incorporating more data as model inputs will assist in conducting more extensive and precise analyses. Finally, the development of hybrid models by integrating diverse approaches and utilizing time-series data can offer broader insights into market behaviors, providing effective assistance to investors and organizations in their decision-making processes.

References

1. Ahmed, Z. and Hla, D. T. (2019). Stock return volatility and capital structure measures of nonfinancial firms in a dynamic panel model: Evidence from Pakistan. *International Journal of Finance & Economics*, 24(1), pp. 604-628. https://doi.org/10.1002/ijfe.1682
2. Al-Slehat, Z. A. F., Zaher, C. and Fattah, A. (2020). Impact of financial leverage, size, and assets structure on firm value: Evidence from industrial sector, *Jordan. International Business Research*, 13(1), pp. 109-120. DOI:10.5539/ibr.v13n1p109
3. Asyik, N. F., Agustia, D. and Muchlis, M. (2023). Valuation of financial reporting quality: is it an issue in the firm's valuation?. *Asian Journal of Accounting Research*, (ahead-of-print). https://doi.org/10.1108/AJAR-08-2022-0251
4. Bhowmik, R. and Wang, S. (2020). Stock market volatility and return analysis: A systematic literature review. *Entropy*, 22(5), p. 522. https://doi.org/10.3390/e22050522
5. Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, 31(3), pp. 307-327. https://doi.org/10.1016/0304-4076(86)90063-1
6. Box, G. E., Jenkins, G. M., Reinsel, G. C. and Ljung, G. M. (2015). Time series analysis: forecasting and control. John Wiley & Sons, U.S. https://www.scirp.org/reference/ReferencesPapers?ReferenceID=1969833
7. Brooks, C. (2014), *Introductory econometrics for Finance (3rd.)*, New York: Cambridge University Press, New York. https://doi.org/10.1017/CBO9781139540872
8. Cenesizoglu, T. (2011). Size, book-to-market ratio and macroeconomic news. *Journal of Empirical Finance*, 18(2), pp. 248-270.
9. Chen, J., Chollete, L. and Ray, R. (2010). Financial distress and idiosyncratic volatility: An empirical investigation. *Journal of Financial Markets*, 13(2), pp. 249-267. https://doi.org/10.1016/j.finmar.2009.10.003
10. Christie, A. A. (1982). The stochastic behavior of common stock variances: Value, leverage, and interest rate effects. *Journal of Financial Economics*, 10(4), pp. 407-432.https://doi.org/10.1016/0304-405X(82)90018-6
11. Ehrmann, M. and Fratzscher, M. (2004). Taking stock: Monetary policy transmission to equity markets. *Journal of Money, Credit and Banking*, 36, pp. 719-737. https://www.jstor.org/stable/3839039
12. Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica: *Journal of the econometric society*, 987-1007. https://doi.org/10.2307/1912773
13. Engle, R. F. and Ng, V. K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance*, 48(5), pp. 1749-1778. https://doi.org/10.1111/j.15406261.1993.- tb05127.x
14. Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, 116(1), pp. 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010

15. Fama, E. F. and French, K. R. (2018). Choosing factors. *Journal of financial economics*, 128(2), 234-252. https://doi.org/10.1016/j.jfineco.2018.02.012
16. Friedmann, R. and Sanddorf-Köhle, W. G. (2002). Volatility clustering and nontrading days in Chinese stock markets. *Journal of Economics and Business*, 54(2), pp. 193-217. https://doi.org/10.1016/S0148-6195(01)00062-5
17. Ghasemzadeh, M., Heydari, M., and Mansourfar, G. (2021). Earning volatility, capital structure decisions and financial distress by SEM. *Emerging Markets Finance and Trade*, 57(9), pp. 2632-2650. https://doi.org/10.1080/1540496X.2019.1663729
18. Glosten, L. R., Jagannathan, R. and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), pp. 1779-1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x
19. Grachev, O. Y. (2017). Application of time series models (ARIMA, GARCH, and ARMA-GARCH) for stock market forecasting. Northern Illinois University, DeKalb, United States. https://huskiecommons.lib.niu.edu/studentengagement-honorscapstones/177
20. Ibhagui, O. W. and Olokoyo, F. O. (2018). Leverage and firm performance: New evidence on the role of firm size. *The North American Journal of Economics and Finance*, 45, pp. 57-82. https://doi.org/10.1016/j.najef.2018.02.002
21. Kashyap, S. (2023). Review on volatility and return analysis including emerging developments: evidence from stock market empirics. *Journal of Modelling in Management*, 18(3), pp. 756-816. https://doi.org/10.1108/JM2-10-2021-0249
22. Kontonikas, A. and Kostakis, A. (2013). On monetary policy and stock market anomalies. *Journal of Business Finance & Accounting*, 40(8), pp. 1009-1042. https://doi.org/10.1111-/jbfa.12028
23. Krause, T. A. and Tse, Y. (2016). Risk management and firm value: recent theory and evidence. *International Journal of Accounting and Information Management*, 24(1), pp. 56-81. https://doi.org/10.1108/IJAIM-05-2015-0027
24. Lam, K. S. (2002). The relationship between size, book-to-market equity ratio, earnings–price ratio, and return for the Hong Kong stock market. *Global finance journal*, 13(2), pp. 163-179. https://doi.org/10.1016/S1044-0283(02)00049-2
25. Li, X., Brooks, C. and Miffre, J. (2009). The value premium and time-varying volatility. *Journal of Business Finance & Accounting*, 36(9-10), pp. 1252-1272. https://doi.org/10.1111/j.1468-5957.2009.02163.x
26. Liu, H. and Shao, S. (2016). India's tea price analysis based on ARMA model. *Modern Economy*, *7*(2), pp. 118-123. https://doi.org/10.4236/me.2016.72014
27. Manzoor, D. and Yadi-Poor, M. (2016). Evaluation and Prediction of Price Fluctuations in the Iranian Electricity Market Using the ARMAX-GARCH Model. *Quantitative Economics Quarterly*, 13(1), pp. 97-117. (In Persian). https://doi.org/10.22055/jqe.2016.12328
28. Mehrara, M. and Abdoli, G. (2006). The Asymmetry of Stock Market Volatility: The Case of Iran. *Iranian Journal of Economic Research*, 8(26), pp. 25-40. https://ijer.atu.ac.ir/article_3706.html?lang=fa
29. Mirzaei, K., Fotouh Abadi, V. and Nosratabadi, J. (2019). Investigating the Factors Affecting Bitcoin Fluctuations and the Inherent Financial Risks in Cryptocurrencies Using the GARCH Model (1,1). *Defense Economics*, 3(10), pp. 131-148. (In Persian). https://doi.org/20.1001.1.25382454.1397.3.10.6.6
30. Modigliani, F., and Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American Economic Review*, 48(3), pp. 261-297.

https://www.jstor.org/stable/1809766
31. Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. Econometrica: *Journal of the econometric society*, 59(2), pp. 347-370. https://doi.org/10.2307/2938260
32. Nourahmadi, M. and Sadeqi, H. (2023). Portfolio Diversification Based on Clustering Analysis. *Iranian Journal of Accounting, Auditing and Finance*, *7(*3), pp. 1-16. https://doi.org/10.22067/ijaaf.2023.43078.1092
33. Nugroho, B. Y. (2020). The effect of book to market ratio, profitability, and investment on stock return. *International Journal Of Economics And Management Studies*, 7(6), pp. 102-107. https://doi.org/10.14445/23939125/IJEMS-V7I6P114
34. Nukala, V. B. and Prasada Rao, S. S. (2021). Role of debt-to-equity ratio in project investment valuation, assessing risk and return in capital markets. *Future Business Journal*, *7*(1), p. 13. https://doi.org/10.1186/s43093-021-00058-9
35. Otaify, M. (2020). Modeling volatility of size, value and financial leverage-sorted portfolios: Evidence from Egyptian stock exchange. *Journal of Public Affairs*, 22(2), A. e2369. https://doi.org/10.1002/pa.2369
36. Park, H. (2019). An intangible-adjusted book-to-market ratio still predicts stock returns. *Critical Finance Review*, 25(1), pp. 207-236. https://cfr.pub/forthcoming/papers/park2019intangible.pdf
37. Pätäri, E., Ahmed, S., Luukka, P. and Yeomans, J. S. (2023). Can monthly-return rank order reveal a hidden dimension of momentum? The post-cost evidence from the US stock markets. *The North American Journal of Economics and Finance*, 65, A. 101884. https://doi.org/10.1016/j.najef.2023.101884
38. Pontiff, J. and Schall, L. D. (1998). Book-to-market ratios as predictors of market returns. *Journal of financial economics*, 49(2), pp. 141-160. https://doi.org/10.1016//S0304-405X(98)00020-8
39. Ramezani Sharif Abadi, M., Aliahmadi, S., Aghabeikzadeh, M. (2022). The effect of Size, Value and Idiosyncratic Risk Anomalieson the Relationship between Tail Risk and Stock Excess Returns. *Iranian Journal of Accounting, Auditing and Finance*, 6(1), pp. 77-90. https://doi.org/10.22067/ijaaf.2022.41544
40. Rønold, A. H. and Hausken, F. O. H. (2018). *A Dynamic ARMA-GARCH Model: Forecasting Returns and Trading at the Oslo Stock Exchange*, Master's thesis, NTNU, Trondheim, Norway. http://hdl.handle.net/11250/2573100
41. Rutkowska-Ziarko, A. (2015). The influence of profitability ratios and company size on profitability and investment risk in the capital market. *Folia Oeconomica Stetinensia*, 15(1), pp. 151-161.https://doi.org/10.1515/foli-2015-0025
42. Shin, H. H. and Stulz, R. M. (2000). Firm value, risk, and growth opportunities. Dice Center Working Paper No. 2000-8, Available at SSRN. https://dx.doi.org/10.2139/ssrn.234344
43. Tahir, S. H., Sabir, H. M., Alam, T. and Ismail, A. (2013). Impact of firm's characteristics on stock return: a case of non-financial listed companies in Pakistan. *Asian Economic and Financial Review*, 3(1), pp. 51-61. https://archive.aessweb.com/index.php/5002/arti-article/view/972
44. Vithessonthi, C. and Tongurai, J. (2015). The effect of firm size on the leverage–performance relationship during the financial crisis of 2007–2009. *Journal of Multinational Financial Management*, 29, pp. 1-29. https://doi.org/10. 1016/j.mulfin. 2014.11.001
45. Vo, X. V. (2015). Foreign ownership and stock return volatility–Evidence from Vietnam. *Journal of Multinational Financial Management*, 30, pp. 101-109. https://doi.org/10.1016/j.mulfin.2015.03.004

46. Vo, X. V. (2016). Does institutional ownership increase stock return volatility? Evidence from Vietnam. *International Review of Financial Analysis*, 45, pp. 54-61. https://doi.org/10.1016/j.irfa.2016.02.006
47. Vuong, G. T. H. and Nguyen , M. H. (2024). Firm value, stock return volatility, and growth opportunity: Insight from an emerging market, *The International Conference on Accounting and Financial Economics*.14(1), pp. 100-118. https://www.researchgate.net/publication/378179986
48. Vuong, G. T. H., Van Nguyen, P., Barky, W. and Nguyen, M. H. (2024). Stock return volatility and financial distress: Moderating roles of ownership structure, managerial ability, and financial constraints. *International Review of Economics & Finance*, 91, pp. 634-652. https://doi.org/10.1016/j.iref.2024.01.054
49. Zabol, M. A. and Abounoori, E. (2020). Evaluation of RGARCH Model to Estimate the Conditional Variance of Tehran Stock Exchange Index. *Journal of Investment Knowledge*, 9(33), pp. 129-145 (In Persian). https://jik.srbiau.ac.ir/article_12379.html?lang=fa