

Çam, Salih; Uzkaralar, Önder; Borak, Metin

Article

Idiosyncratic risk and market volatility: Threat or opportunity for returns? A study of Borsa Istanbul stocks

Borsa İstanbul Review

Provided in Cooperation with:

Borsa İstanbul Anonim Şirketi, İstanbul

Suggested Citation: Çam, Salih; Uzkaralar, Önder; Borak, Metin (2024) : Idiosyncratic risk and market volatility: Threat or opportunity for returns? A study of Borsa Istanbul stocks, Borsa İstanbul Review, ISSN 2214-8469, Elsevier, Amsterdam, Vol. 24, Iss. 4, pp. 698-709, <https://doi.org/10.1016/j.bir.2024.04.001>

This Version is available at:

<https://hdl.handle.net/10419/340495>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by-nc-nd/4.0/>



Idiosyncratic risk and market volatility: Threat or opportunity for returns? A study of Borsa Istanbul stocks

Salih Çam^{a,*}, Önder Uzkaralar^b, Metin Borak^c

^a Cukurova University, Faculty of Administrative Sciences and Economics, Department of Econometrics, Adana, Türkiye

^b Osmaniye Korkut Ata University, Faculty of Administrative Sciences and Economics, Department of Business Administration, Osmaniye, Türkiye

^c Cukurova University, Faculty of Administrative Sciences and Economics, Department of Business Administration, Adana, Türkiye

ARTICLE INFO

Keywords:

Idiosyncratic risk
Market volatility
Stock returns

ABSTRACT

This study investigates the relationship between idiosyncratic risk, market volatility, and stock returns for companies traded on the Borsa Istanbul. The analysis calculates idiosyncratic risk and market volatility and estimates the coefficients using cross-sectional and panel data approaches. The GARCH and EGARCH models are used to calculate market volatility, while idiosyncratic risk is measured using the Capital Asset Pricing Model, and three-factor, four-factor, and five-factor models. We run the Fama-MacBeth regression to investigate the cross-sectional relationship between idiosyncratic risk, market volatility, and stock returns and the Arellano-Bover/Blundell-Bond panel regression technique to unveil firm-specific effects. The estimated coefficients demonstrate a positive relationship between idiosyncratic risk and stock returns and a negative relationship between market volatility and stock returns. Furthermore, the findings suggest that larger firm size, higher trading volume, higher market returns, and higher book-to-market ratios have positive effects, while beta and corporate governance indices have negative effects on returns.

1. Introduction

In his seminal work, Markowitz (1952) proposed a mathematical framework establishing the relationship between risk and return, which led to the emergence of many financial models that attempt to uncover the impact of risk on return (Merton, 1973; Sharpe, 1964). Based on this theoretical background, most financial models postulate a positive relationship between market risk and returns in market equilibrium (Chou, 1988; French et al., 1987). In this context, extensive empirical literature has emerged that endeavors to confirm this equilibrium relationship. However, a conclusive consensus on this topic remains elusive (Chabi-Yo, 2011; Fink et al., 2012; Schwert, 1989; Turner et al., 1989; Whitelaw, 1994). Empirical studies often report insignificant or even negative relationships between risk and returns (Glosten et al., 1993; Nelson, 1991; Qadan et al., 2019). Despite the strong theoretical correspondence between risk and returns (Campbell, 1987; Merton, 1980; Pindyck, 1984; Scruggs, 1998), the inability to observe this relationship may be due to imprecise risk measures and market imperfections. However, regardless of how risk is measured (Bowman, 1979; Gençay et al., 2005; Hong & Sarkar, 2007; Reeb et al., 1998) or whether

empirical evidence supports the theoretical relationship, the influence of risk on stock returns cannot be ignored.

Although financial theories have long shown an interest in the impact of risk on returns, they have primarily focused on market risks. However, in the financial context, risk is divided into two main components: market risk and idiosyncratic risk (Beja, 1972; Rowe & Kim, 2010). Market risk, which cannot be mitigated through diversification (Li et al., 2019; Silva et al., 2017; Yang et al., 2020), is caused by factors beyond the control of investors and firms. In contrast, idiosyncratic risk, which can be mitigated through diversification (Iqbal & Shah, 2012; Zaimovic et al., 2021), refers to risks that are specific to individual firms or industries (Goyal & Santa-Clara, 2003; Mazumdar et al., 2020). While each risk component presents potential challenges and opportunities for investors, the interaction between idiosyncratic risk and market volatility is crucial in financial markets, particularly with respect to the dynamics of emerging markets. Modern finance theory assumes that investors invest in diversified portfolios to minimize idiosyncratic risk. Building on this assumption, the Capital Asset Pricing Model (CAPM) and the three-, four-, and five-factor models extend portfolio theory by assuming that all investors hold market portfolios in equilibrium. This

Peer review under responsibility of Borsa İstanbul Anonim Şirketi.

* Corresponding author. Cukurova University, Faculty of Administrative Sciences and Economics, Department of Econometrics, Adana, Türkiye.

E-mail addresses: scam@cu.edu.tr, camsalih01@gmail.com (S. Çam), onderuzkaralar@osmaniye.edu.tr (Ö. Uzkaralar), mborak@cu.edu.tr (M. Borak).

<https://doi.org/10.1016/j.bir.2024.04.001>

Received 29 December 2023; Received in revised form 3 April 2024; Accepted 3 April 2024

Available online 10 April 2024

2214-8450/© 2024 Borsa İstanbul Anonim Şirketi. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

assumption implies that only systematic risk is priced in equilibrium, whereas idiosyncratic risk remains unpriced. However, in practice, perfectly diversified portfolios are unattainable because of various factors such as market imperfections, transaction costs, information constraints, investor behavior, and budget constraints. Thus, excluding idiosyncratic risk from asset pricing poses a significant structural problem. To mitigate these problems, idiosyncratic risk has been incorporated into asset-pricing models, and empirical studies have shown that idiosyncratic risk is a significant component of returns (Au et al., 2009; Huang et al., 2010; Liu, 2022; Long et al., 2018; Long et al., 2020). Ultimately, although the relationship between idiosyncratic risk and market risk and returns is well established theoretically, the empirical effects of both risks on returns are inconsistent because of the many factors that can affect the risk–return relationship, such as market dynamics, analysis period, data frequency, and risk calculation method (Ang et al., 2006; Brown & Ferreira, 2016; Chen & Petkova, 2012; Chua et al., 2010; Fu, 2009; Gu et al., 2018; Hur et al., 2014; Khovansky & Zhylyevskyy, 2013; Malkiel and Xu 1997, 2004; Shi et al., 2016; Spiegel & Wang, 2005). Therefore, a more nuanced understanding requires recognition of the complexity of this relationship in real markets.

Motivated by the established impact of idiosyncratic risk and market volatility on stock returns, this study investigates the risk–return association in the context of emerging markets. Specifically, 202 stocks listed on the Borsa Istanbul are analyzed in this study to examine the impact of idiosyncratic risk and market volatility on stock returns, as previous research has been inconclusive (Bali & Cakici, 2008; Fazil & İpek, 2013). Given the robust nature of the relationship between market volatility, idiosyncratic risk, and stock returns, a nuanced examination in a specific context is essential. In this context, this study aims to empirically establish the relationship between risk and return, focusing on the unproven impact of risk factors on the returns of individual stocks, especially in the context of emerging stock markets such as Borsa Istanbul. Rigorous empirical evidence on the relationship between idiosyncratic risk, market risk, and return is not only a valuable guide for investors but also an important reference for researchers in the field of investment analysis. This study uses the GARCH and EGARCH models to measure market volatility and the CAPM, and three-factor, four-factor, and five-factor models to calculate idiosyncratic risk. Quarterly idiosyncratic risk data from January 1, 2010, to June 30, 2023, are derived from daily closing price series, resulting in 54 quarterly observations for each stock. The complicated nature of the risk–return series requires an examination of both cross-sectional and time-series information. Based on this principle, various econometric techniques have been used to capture the complex risk–return relationship. The cross-sectional analysis utilizes the two-stage regression model of Fama and MacBeth (1973). In this approach, the coefficients of individual companies are estimated through a time-series analysis and then used to determine the coefficient of the relevant factor in the second stage. Additionally, the Arellano–Bover/Blundell–Bond dynamic panel regression model, which captures the time dimension of an individual firm, is used to uncover firm-specific information. This dual approach allows a thorough evaluation of both cross-sectional and panel data for the stocks listed on Borsa Istanbul. As a result, the analysis in this study incorporates six risk measures, including GARCH and EGARCH market volatility measures, and four idiosyncratic risk indicators derived from the CAPM and factor models. To ensure robustness, each model is estimated using three partial regressions, considering positive excess returns, negative excess returns, and all observations separately. This multidimensional perspective, characterized by different risk measures (idiosyncratic and market) and including both horizontal (cross-sectional) and vertical (panel data) analyses, distinguishes this study from the existing literature and provides a more nuanced understanding of the risk–return relationship on Borsa Istanbul.

2. Idiosyncratic risk

In the broadest sense, risk refers to deviations from expectations and inherently involves probabilistic uncertainty about the future. In the financial context, risk measures the uncertainty that an investor is willing to accept to realize a return on an investment. The concept contains many ambiguities in its definition and has no universally accepted framework; therefore, no unique method for computing risk exists. In the financial context, risk comprises two components: market-driven risk and idiosyncratic risk. Therefore, when market risk is decomposed, what remains is idiosyncratic risk.

2.1. The CAPM

The CAPM, introduced by William Sharpe (1964) and John Lintner (1965), is among the most widely used and accepted models for pricing financial assets. This single-factor equilibrium model investigates the relationship between systematic risks and returns. Consequently, the model includes only market-related components (Bali et al., 2005; Bozhkov et al., 2020). Since total equity risk is the sum of market-driven and idiosyncratic risks, idiosyncratic risk can be measured as the residual variance of equity returns after subtracting systematic risk. The basic mathematical formulation of the CAPM is as follows:

$$R_{i,t} - r_{f,t} = \alpha + \beta_1 (R_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad (1)$$

where $r_{f,t}$ is the risk-free rate of return, β_1 is the slope coefficient estimated from the regression model and is equal to $\frac{\text{cov}(R_{i,t}, R_{M,t})}{\text{var}(R_{M,t})}$, and $\varepsilon_{i,t} \sim (\sigma^2, 0)$ are the error terms that include only firm-specific risks (Fabozzi et al., 2007). The variable related to the market is included in the regression model; therefore, no market-specific effect in the residuals is obtained from the regression. Thus, the standard deviation of the residuals in Eq. (1) represents idiosyncratic risk.

2.2. The three-factor model

The CAPM is based on strict assumptions, such as investors' general expectations, unlimited borrowing and lending at a risk-free rate, and no transaction costs. The strict assumptions and single factors explaining returns have led to criticism of the model. Researchers have argued that the returns for securities cannot be explained by the market beta alone and that factors such as book-to-market (Chan et al., 1991), size (Banz, 1981), and price-earnings ratio (Basu, 1977) should also be considered when valuing an asset. To overcome the shortcomings of the CAPM, Fama and French (1993) proposed a three-factor model that included book-to-market and market factors. The three-factor model proposed by Fama and French (1993) is expressed as follows.

$$R_{i,t} - r_{f,t} = \alpha + \delta_1 (R_{m,t} - r_{f,t}) + \delta_2 SMB_{i,t} + \delta_3 HML_{i,t} + \varepsilon_{i,t} \quad (2)$$

where $R_{i,t}$ is the return on the i -th share in month t , $SMB_{i,t}$ is the difference between the returns on the portfolios with small-cap shares and the returns on the portfolios with large-cap shares at time t , and $HML_{i,t}$ is the difference between the returns of portfolios containing stocks with high book-to-market ratios and the returns of portfolios containing stocks with low book-to-market ratios at time t . In addition, α and δ_i for $i = (1, 2, 3)$ are the constant and slope coefficients, respectively, while $\varepsilon_{i,t} \sim (\sigma^2, 0)$ is residuals that include only firm-specific effects. Thus, $IV_i = \sqrt{\text{var}(\varepsilon_{i,t})}$ is the idiosyncratic risk of i -th stock in period t (Ali et al., 2020).

2.3. The four-factor model

The efforts to value financial assets did not end with the three-factor model. Carhart (1997) found that the three-factor model does not capture the momentum factor and suggested adding a momentum factor

that captures the Jegadeesh and Titman (1993) momentum anomaly in addition to the three factors. Consequently, a four-factor model was constructed. The model specifications are as follows:

$$R_{i,t} - r_{f,t} = \gamma + \varphi_1 (R_{m,t} - r_{f,t}) + \varphi_2 SMB_{i,t} + \varphi_3 HML_{i,t} + \varphi_4 WML_{i,t} + \omega_{i,t} \quad (3)$$

where, in addition to the three-factor model, $WML_{i,t}$ is the difference between the returns of the portfolios containing the stocks of the former winners and the returns of the portfolio containing the stocks of the former losers at time t . Moreover, γ is the constant coefficient and φ_i for $i = (1, 2, 3, 4)$ are slope coefficients obtained by regression estimation; $IV_i = \sqrt{\text{var}(\omega_{i,t})}$ is the idiosyncratic risk of the i th stock in period t .

2.4. The five-factor model

Fama and French (2015) developed a five-factor model as an extension of their earlier three-factor model to improve the understanding of stock returns. Profitability and investment portfolios are added to the three-factor model, according to the following model specifications:

$$R_{i,t} - r_{f,t} = \varphi + \vartheta_1 (R_{m,t} - r_{f,t}) + \vartheta_2 SMB_{i,t} + \vartheta_3 HML_{i,t} + \vartheta_4 RMW_{i,t} + \vartheta_5 CMA_{i,t} + v_{i,t} \quad (4)$$

where $CMA_{i,t}$ represents the difference between the return of portfolios with low-investing stocks, called conservative, and the return of portfolios with high-investing stocks, called aggressive, at time t . Moreover, φ represents the constant of the model and ϑ_i for $i = (1, 2, 3, 4, 5)$ are the slope coefficients derived from regression estimation. All the asset pricing models described above have evolved from the CAPM to the five-factor model. Although these models all include market-related factors, they lack the firm-specific factors that constitute idiosyncratic risk. Therefore, regardless of their explanatory power, the residuals obtained from these models contain only firm-specific information. Thus, it is plausible to compute idiosyncratic risk from the error terms that exclude all market-related information. Consequently, the analysis results can be used to determine whether the models produce different results in practice, although it is difficult to determine which model is superior.

3. Analysis and results

Despite these inconclusive results, the effects of market volatility and idiosyncratic risk on returns cannot be ignored. Estimating the unique and isolated effects of risk on returns requires a robust regression framework and the relevant control variables. In this context, this study applies well-established techniques from the financial literature and integrates several commonly used control variables, including market volatility (Chung & Chuwonganant, 2018; Irshad, 2017; Ma et al., 2018), market-to-book ratio, beta and firm size (Fama & French, 1992; Pontiff & Schall, 1998; Heston et al., 1999; Fletcher, 2000; Drew, 2003; Cordeiro da Cunha Araújo and André Veras Machado 2018), trading volume of index (Chen, 2012; Lee & Rui, 2000), and corporate governance (Cremers & Nair, 2005; Durnev et al., 2003; Ferreira & Laux, 2007; Gompers et al., 2003; Morck et al., 2000) to obtain robust coefficient estimates for the risk factors of interest. Concordantly, the analysis begins by decomposing total equity risk into its systematic and idiosyncratic components. Subsequently, the coefficients of the explanatory variables are calculated through an econometric estimation process, including the two-stage cross-sectional approach of Fama and MacBeth (1973) and Arellano-Bover/Blundell-Bond dynamic panel regression models. Among the explanatory variables, beta, market-to-book ratio, firm size, trading volume of Borsa Istanbul, and the corporate governance index are included as control variables in the regression models to estimate the unbiased coefficients for idiosyncratic risk and market volatility. Daily closing prices from January 1, 2010, to

June 30, 2023, are utilized to calculate the idiosyncratic risk of the stocks. The closing prices and associated factor observations are divided into quarterly subsets to calculate quarterly idiosyncratic risk.¹ Finally, for each stock series, 54 models are calculated based on the 54 data subsets. The regression models are estimated to include one of the calculated idiosyncratic risk measures based on the CAPM and the three-, four-, and five-factor models, as described in the previous section. Once the firm-based risk is calculated from these models, the final step is to establish the relationship between idiosyncratic risk, market volatility obtained from the GARCH and EGARCH models, and stock returns using the Fama–MacBeth two-stage regression which provides a cross-sectional analysis via the slope of the coefficients of each risk factor used in the model, and the Arellano-Bover/Blundell-Bond panel regression approach, which provides a time- and unit-dimensional analysis.

Table 1 summarizes the descriptive statistics and correlation matrices of the variables. All variables except RM, EXR, and RS were used in logarithmic form. IR_C is the idiosyncratic risk series derived from the CAPM, IR_3F is the idiosyncratic risk series based on the three-factor model, and IR_4F and IR_5F are the idiosyncratic risk series derived from the four- and five-factor models, respectively. CRP represents the corporate governance index of Borsa Istanbul and SZ represents the size of the company. BT is the beta of stocks and MB is the market-to-book series. Where RM is the market return, RS is the series of individual stock returns, EXR is the excess return calculated as (RM-RS), and VLM is the trading volume of Borsa Istanbul. Finally, VLT is the volatility series of Borsa Istanbul, obtained from the GARCH and EGARCH² models. Although four models are employed to compute idiosyncratic risk, all idiosyncratic risk series have similar means, standard deviations, and minimum values. IR_C has the largest standard deviation among the other idiosyncratic risk measures. This result is not unexpected because the CAPM contains only beta and market returns. The more explanatory variables included in an econometric model, the greater the dispersion of the error terms around zero. Therefore, the standard deviation decreases as the number of factors in the model increases. The correlation matrix is presented at the end of Table 1. In an econometric model, the correlation between explanatory variables should be zero. However, in practice, it is almost impossible for the variables to remain uncorrelated. This is because economic and financial data are typically influenced by the same factors; therefore, the correlation between them is typically high. A high correlation leads to several problems in coefficient estimation, such as biased coefficient estimation or the inability to determine the unique effects of independent variables on the dependent variable. Therefore, if the variables do not have high correlation coefficients, the estimated coefficients in the regression model do not cause such a bias. Accordingly, the covariance matrix entries in Table 1 are generally low or moderate. The highest correlation coefficient is calculated between company size and the corporate governance index. However, even this coefficient falls below 50%.

Table 2 presents the estimated coefficients on the GARCH and EGARCH models derived from the residuals of the ARMA (5,4) regression. Notably, the ARCH and GARCH terms have statistically significant coefficients in both models. However, it is crucial to recognize that the ARCH/GARCH framework and its derivatives rely on the assumption of homoscedastic (white noise) residuals. Therefore, using a volatility series generated by such models requires rigorous diagnostic tests. In this study, the ARCH test for heteroscedasticity and the autocorrelation function (ACF) test were applied. The results confirm the

¹ All other explanatory variables, including the dependent variable, were obtained as quarterly data from the Finnet database.

² The ARMA (5,4) model was used to obtain the market volatility series of the Borsa Istanbul, and thus 1420 observation vanished. According to the AIC and SIC information criteria, GARCH and E-GARCH(1,1) is the best model to capture the volatility series.

Table 1

Descriptive statistics and correlation matrix.

Variable	Obs.	Mean	Std. Dev.	Min	Max
IR_C	7668	2.319	1.294	0.303	62.154
IR_3F	7668	2.221	1.105	0.280	34.714
IR_4F	7668	2.188	1.053	0.279	24.388
IR_5F	7668	2.162	1.029	0.277	21.543
SZ	7668	20.049	1.933	15.009	26.312
BT	7668	−0.243	0.242	−1.825	0.316
VLM	7668	26.828	1.132	25.469	29.687
MB	7628	0.630	0.872	−2.028	6.382
VLT	6248	4.110	1.129	2.300	6.866
CRP	7668	6.757	0.507	6.079	8.402
RM	7526	0.057	0.153	−0.207	0.739
RS	7526	0.099	0.340	−0.799	6.692
EXR	7526	0.042	0.302	−1.097	6.657

Correlation Matrix								
	IR_5F	VLT	MB	BT	SZ	RM	CRP	VLM
IR_5F	1							
VLT	0.170	1						
MB	0.210	0.114	1					
BT	0.113	0.121	0.104	1				
SZ	−0.057	0.175	0.387	0.325	1			
RM	0.135	0.278	0.223	0.129	0.223	1		
CRP	0.297	0.365	0.308	0.283	0.430	0.377	1	
VLM	0.128	0.280	0.085	0.043	0.089	0.524	0.081	1

Table 2

The coefficients of GARCH and EGARCH models.

Variable	GARCH		EGARCH	
	Coeff.	Prob.	Coeff.	Prob.
Mu	0.024	0.0000	0.027	0.0074
AR(1)	0.203	0.0867	0.030	0.8230
AR(2)	−0.272	0.0125	−0.021	0.8521
AR(3)	−0.099	0.4826	−0.025	0.7833
AR(4)	−0.301	0.0000	−0.478	0.0000
AR(5)	−0.123	0.1347	−0.192	0.0702
MA(1)	−0.387	0.0000	−0.198	0.0000
MA(2)	0.564	0.0000	0.213	0.0000
MA(3)	−0.377	0.0000	−0.202	0.0000
MA(4)	0.821	0.0000	0.837	0.0000
Omega	0.001	0.9994	0.326	0.0000
Alpha	0.239	0.0494	−0.271	0.0000
Beta	0.761	0.0000	1.003	0.0000

Diagnostic Tests				
	Coeff.	Prob.	Coeff.	Prob.
ARCH Test	0.178	0.6754	0.664	0.4195
Autocorrelation				
1	−0.063	0.657	−0.118	0.3960
2	−0.229	0.244	−0.184	0.2840
3	0.010	0.419	−0.117	0.3530
4	0.092	0.512	0.056	0.4870
5	−0.113	0.555	−0.046	0.6150
6	−0.037	0.671	−0.050	0.7170
7	0.063	0.749	0.024	0.8100
8	−0.097	0.778	−0.038	0.8730

homoscedasticity of the residuals and the absence of statistically significant ACF values up to lag 8. Thus, the error terms of the estimated models are consistent with the a priori assumptions.

Cross-sectional and panel data analyses are utilized to establish a relationship between idiosyncratic risk, market volatility, and individual stock returns³; however, market returns and market volatility have time-series properties because they are repeated for each stock. The line charts of the market volatility series obtained from the GARCH and EGARCH models and the market returns in Fig. 1 show fluctuations in the variables during the analysis period. In the market volatility series, the first six observations are excluded because of the lagged variables included in the ARMA, GARCH, and EGARCH models. The red lines in the charts present four-week moving averages of the corresponding series. The chart shows that the market experienced three distinct periods of significant volatility over the investigated period. Notably, these periods coincide with instances of either significant market gains or substantial losses. In summary, this chart supports the notion that increased risk exposure in financial markets has the potential for both substantial gains and losses.

The dynamic nature of idiosyncratic risk necessitates consideration of different calculation methods, resulting in potential discrepancies in the computed risk series. Fig. 2 shows four distinct idiosyncratic risk series computed using capital asset pricing and three-factor, four-factor, and five-factor models. Notably, none of these models explicitly incorporates firm-specific components. Factor models, especially the CAPM, have a market-oriented perspective and use market factors as explanatory variables. Consequently, the model residuals encapsulate the combined effects of all the excluded factors. The error terms primarily reflect firm-specific fluctuations by including all relevant market variables. Essentially, removing the market contribution to the total stock price variation isolates the firm-specific component. Therefore, the

³ A panel data contains numerous observations for each sampling unit. Such datasets are constructed by merging time series observations from different cross-sectional units such as countries, states, regions, firms or randomly selected individuals or households (Baltagi, 1998, p. 13). However, variables such as market returns are the same for each unit. For example, the market returns on January 1, 2015 is the same for all stocks, regardless of the return of individual stocks on January 1, 2015. Therefore, series such as market returns are repeated for each unit in the panel.

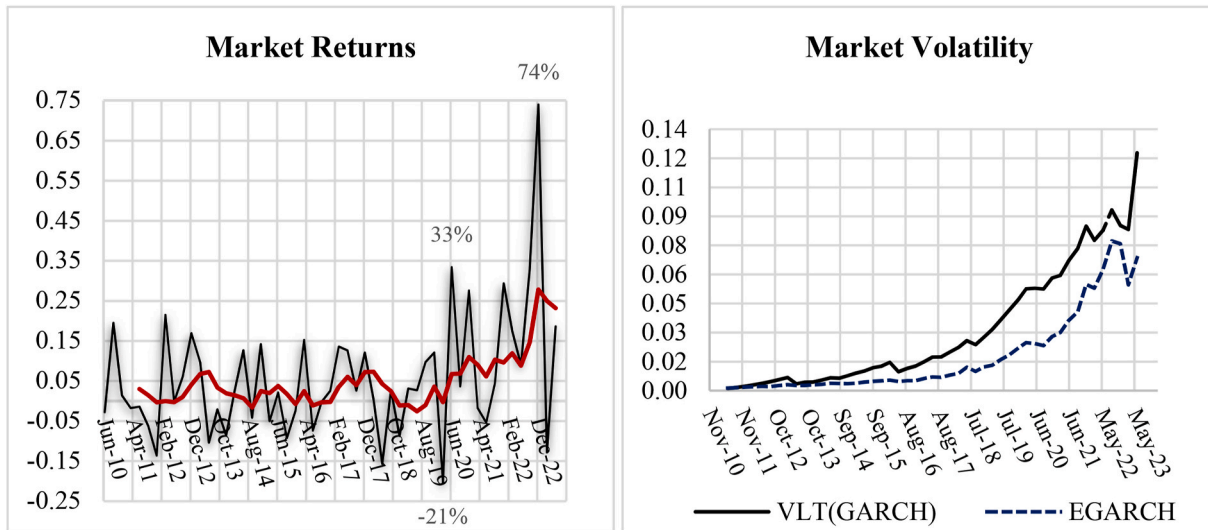


Fig. 1. Market returns and market volatility series.

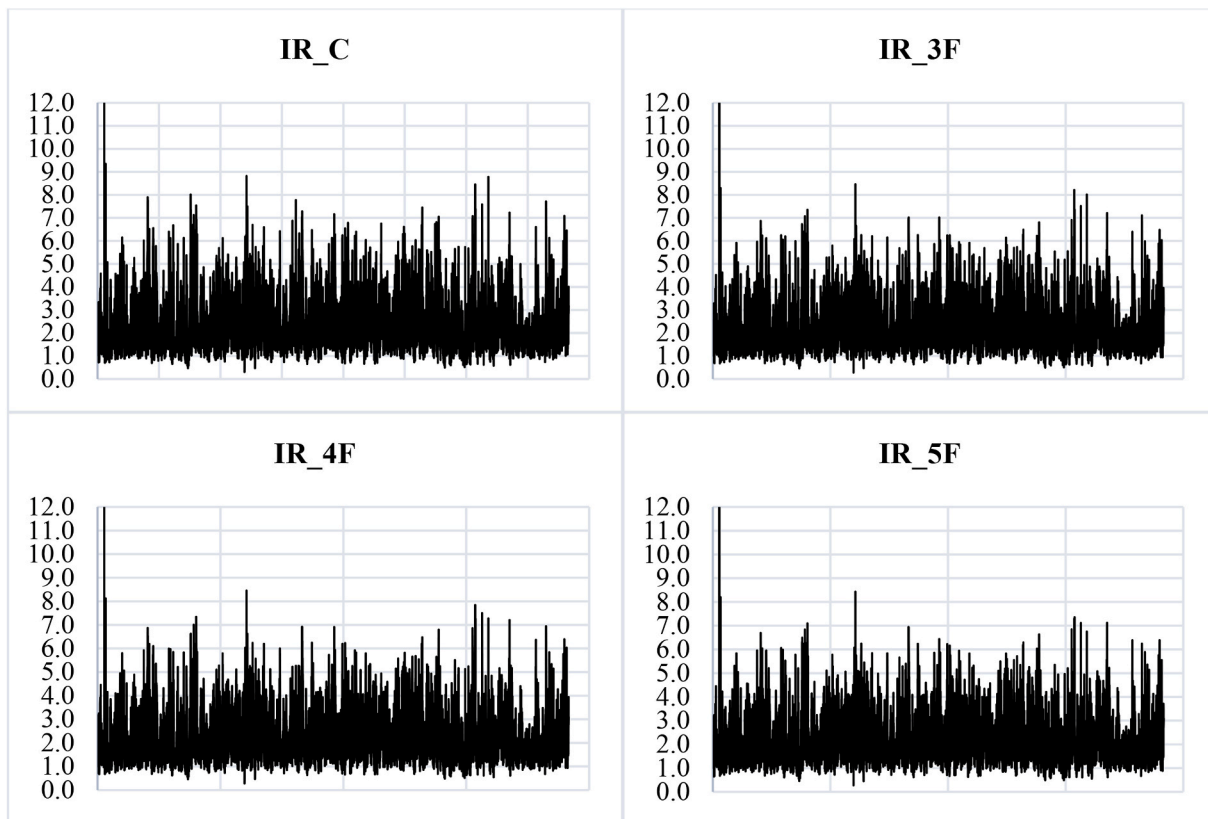


Fig. 2. Idiosyncratic risk based on the CAPM and the three-factor, four-factor, and five-factor models.

standard deviations of the error terms derived from the CAPM and other factor models effectively serve as proxies for idiosyncratic risk.

Idiosyncratic risk is not directly observable. However, implementing theoretical models can provide a measure of idiosyncratic risk. Unfortunately, even if guided by, no unique method is available for calculating idiosyncratic risks. Furthermore, no clear evidence indicates which calculation method is superior. All that can be done is determine idiosyncratic risks using reasonable methods and compare them. In this context, although the idiosyncratic risk series in Fig. 2 have the characteristics of noisy data, their distributions are similar. The series

exhibits different maximum and minimum values; however, their histograms indicate that the risk distributions are nearly identical. For all four series, the predominant occurrence is consistently in the range of 1–2, and each series has a right-skewed distribution. Observations of idiosyncratic risk are rarely distributed in the lower and upper tails. Fig. 3 supports these findings. A careful examination of the figures shows very few observations greater than six or close to zero. The uniform distribution and scatter plots observed for all firm-specific risk series suggest that regression models that include various measures of idiosyncratic risk as explanatory variables are likely to produce consistent

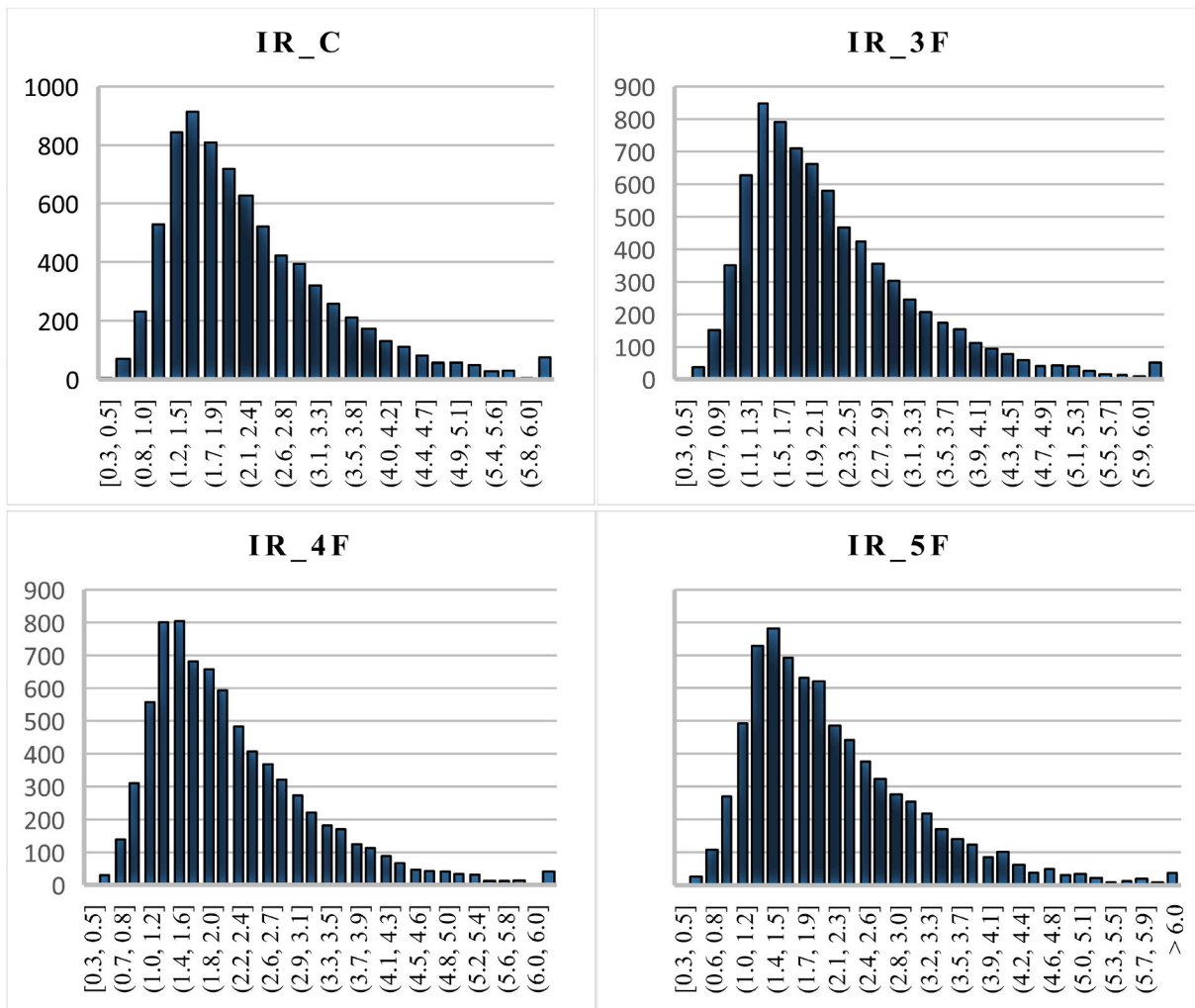


Fig. 3. Distribution of idiosyncratic risks from the CAPM and factor models.

estimation results.

Fig. 4 (upper-left quadrant) provides a three-dimensional visualization of the complex interaction between idiosyncratic risk and stock returns. The IR_5F series is used as a representative measure of idiosyncratic risk. As the idiosyncratic risk measures derived from four different models have high pairwise correlation coefficients, a single risk measure is used for the charts. During periods when stocks have low idiosyncratic risk, returns fluctuate only slightly. Conversely, as idiosyncratic risk increases, the magnitude of the returns or losses gradually increases. The striking conclusion is that, as the magnitude of stock returns increases, the returns become more volatile. As idiosyncratic risk increases, so does its variability. In particular, idiosyncratic risk remains stable at lower levels, but becomes increasingly pronounced and volatile at higher levels. The chart also indicates a positive correlation between idiosyncratic risk and returns. Accordingly, stock returns tend to increase when market returns and idiosyncratic risk increase and volatility tends to increase when the level of returns increases. Furthermore, the second part of the chart shows that individual stock returns are higher when market volatility increases. The density of individual stock returns increases with market volatility and idiosyncratic risk. Simultaneously, stock returns become more volatile when market volatility is high. However, the relationship between market volatility and stock returns is inversely U-shaped. Stock returns tend to increase to the midpoint of market volatility and decrease from a point of market volatility. The effect of the corporate governance index on stock returns follows a similar path. As corporate governance increases, average expected stock

returns also increase. Thus, an inverted U-shaped relationship exists between corporate governance and stock returns.

Although data visualization provides valuable insights into the relationships between variables, econometric methods such as panel data, cross-sectional, or time-series analyses are required to establish these relationships. Here, Fama and MacBeth's (1973) procedure is utilized to construct a cross-sectional relationship between market volatility, idiosyncratic risk, and stock returns. Accordingly, Table 3 summarizes the estimated coefficients from the two-stage Fama-MacBeth cross-sectional regression model. Each model utilizes a different measure of market risk, derived from either the GARCH or EGARCH model and one of the four measures of idiosyncratic risk. This comprehensive approach ensures a rigorous examination of the risk–return relationship by considering both firm-specific and market-based risk components. The coefficients show a consistently positive and statistically significant relationship between the risk premiums associated with idiosyncratic risk factors and stock returns across all models. This result is consistent with theoretical expectations and empirical evidence from previous research (e.g., Merton, 1980). Specifically, higher idiosyncratic risk implies firm-specific uncertainties that market exposure alone cannot mitigate. Consequently, investors demand higher expected returns (risk premium) to compensate for the non-diversifiable risk. Notably, the coefficients are consistent across the models that incorporate both GARCH- and EGARCH-based market risk measures, underscoring the robustness of this relationship. These results validate the effectiveness of the GARCH and EGARCH models in capturing the dynamics of market

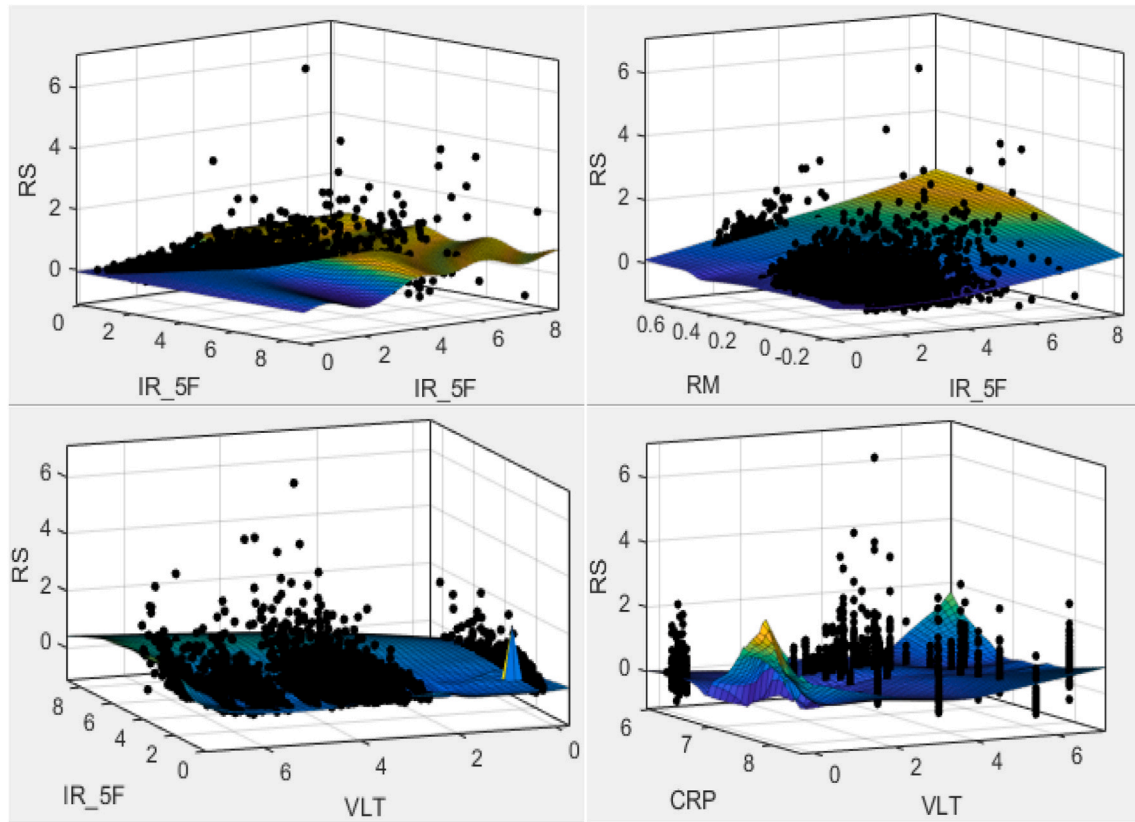


Fig. 4. Idiosyncratic risk, stock returns, market returns and market volatility.

Table 3

Coefficients of the Fama-MacBeth (1973) two-step cross-sectional regressions.

Variable	IR_C		IR_3F	
	GARCH	EGARCH	GARCH	EGARCH
IR	0.0489**	0.0500**	0.0463*	0.0491**
VLT	−0.0999***	−0.1004**	−0.1015***	−0.1023**
RM	0.0219*	0.0234*	0.0226*	0.0241*
SZ	0.1755**	0.2106**	0.1774**	0.2153**
BT	−0.0079*	−0.0088*	−0.0081*	−0.0090*
MB	0.0435	0.0484	0.0432	0.0489
CRP	0.0217	0.0350	0.0217	0.0361
VLM	0.0243*	0.0295*	0.0248*	0.0302**
C	0.0077*	0.0092*	0.0079*	0.0095**
Variable	IR_4F		IR_5F	
	GARCH	EGARCH	GARCH	EGARCH
IR	0.0417**	0.0458**	0.0448*	0.0483**
VLT	−0.1023***	−0.1029***	−0.1015***	−0.1022**
RM	0.0225**	0.0241*	0.0225**	0.0240**
SZ	0.1726**	0.2129**	0.1759**	0.2149**
BT	−0.0083*	−0.0091*	−0.0083*	−0.0092*
MB	0.0411	0.0476	0.0425	0.0485
CRP	0.0201	0.0354	0.0218	0.0367
VLM	0.0243*	0.0301*	0.0246*	0.0302*
C	0.0078*	0.0094*	0.0078*	0.0095*

The (***), (**), and (*) indicate statistical significance levels of 1%, 5%, and 10%, respectively. This study examines the relationship between idiosyncratic risk and individual stock returns using two sets of regression models. In one set of models, market volatility is estimated using a GARCH model, while in the other set, it is estimated using an EGARCH model. These estimated volatilities are included as independent variables in the regressions. In addition, four different measures of idiosyncratic risk are used: IR_C from the CAPM model, IR_3 from the 3-factor model, IR_4 from the 4-factor model, and IR_5 from the 5-factor model.

volatility and its influence on the risk-return relationship.

Accordingly, the VLT coefficients obtained from either the GARCH or EGARCH across all eight models are consistently negative, indicating a statistically significant inverse relationship between market volatility and expected stock returns. This finding suggests that, on average, higher market volatility is associated with lower expected returns for the studied stocks. The magnitude of this association is quantified using coefficient values, which are approximately -0.1% . A 1% increase in market volatility is associated, on average, with a 0.1% decrease in expected stock returns. This is consistent with well-established empirical evidence in financial markets (Fig. 4). Higher market volatility implies greater uncertainty and risk, leading investors to demand higher risk premia (i.e., compensation for assuming increased risk) for holding risky assets such as equities. Consequently, expected returns decline as market volatility increases, reflecting a trade-off between risk and returns. However, the estimated coefficients of the SZ and VLM variables have positive signs consistently in all models. This indicates that stocks tend to generate higher returns during periods characterized by larger and more active market conditions. Conversely, the coefficient on BT consistently has a negative and statistically significant sign, indicating that increased market exposure is associated with lower stock returns. In addition, the control variables MB and CRP do not have statistically significant coefficients in any of the models.

Empirical analyses using cross-sectional, time-series, and panel data usually require preliminary investigations to ensure model fit and data integrity. This study uses a panel data approach in conjunction with a cross-sectional regression. Within this framework, the analysis begins with the necessary pre-tests for panel data to ensure model consistency and establish a valid relationship between variables. To establish such a relationship, the panel data analysis begins with an examination of the cross-sectional dependence of the dependent and independent variables. In this study, the Breusch-Pagan LM and Pesaran CD tests are used to examine the cross-sectional dependence of the variables employed in the

Table 4

Cross-sectional dependency tests.

Variable	Breusch-Pagan LM	Pesaran CD	Prob.
RS	78698.04	253.069	0.0000
EXR	21837.79	67.927	0.0000
SZ	371845.60	602.659	0.0000
MB	98945.89	194.465	0.0000
BT	171958.60	250.799	0.0000
IR_C	41391.97	153.732	0.0000
IR_3F	38852.08	146.125	0.0000
IR_4F	38681.51	146.027	0.0000
IR_5F	39131.74	147.605	0.0000

regression models. Table 4 presents the test results for all variables except the corporate governance, market return, trading volume of Borsa Istanbul, and market volatility series. The omission of a test for cross-sectional dependence for these series is because of their inherent time-series characteristics. These variables have an artificial panel data structure that is specifically influenced by the overall market and replicated for each stock. For example, the market volatility values in the first quarter of 2010 or the last quarter of 2020 are identical for all stocks. Therefore, the conventional panel unit root test is inappropriate for testing the unit roots of these variables. Instead, a time-series unit root test is more appropriate for examining the unit roots of the variables of corporate governance, market returns, and market volatility.

The null hypothesis of “no cross-sectional dependence” is rejected for all variables listed in Table 4 based on the Breusch-Pagan LM and Pesaran CD tests. This indicates cross-sectional dependence among the variables, which requires the application of second-generation unit root tests specifically designed for such scenarios. Consequently, the CADF and CIPS tests developed by Pesaran (2007) are used to assess the variables’ stationarity. In addition, ADF with breakpoints and Ng-Perron unit root tests are applied to the corporate governance index, market returns, and market volatility for time-series analysis. The choice of an

appropriate unit root test is crucial because an incorrect specification can lead to spurious regressions. Applying an inappropriate test to a truly stationary series ($I(0)$) can falsely identify it as non-stationary, thereby leading to a “spurious regression” where a unit root is artificially induced during differencing. This differencing process not only eliminates valuable information but also risks biasing the coefficient estimates or obscuring potentially significant relationships between the variables. To eliminate this drawback, four different unit root tests were performed.

Table 5 provides a comprehensive overview of the results of both the panel and time-series unit root tests. The first section of the table presents the critical values for the CIPS and CADF unit root tests that are generally accepted and used for panel data analyses. Each of these unit root tests is run under two model specifications: one containing only the constant and the other containing both the trend and the constant. Notably, the idiosyncratic risk series derived from the CAPM and three-factor, four-factor, and five-factor models had similar test statistics. The null hypothesis for the CIPS and CADF unit root tests is decisively rejected at conventional significance levels. Stock returns, excess returns, firm size, and the market-to-book ratio are also found to be stationary at the order of zero ($I(0)$). A notable exception is the beta series, in which the null hypothesis of stationarity is not rejected at the level, but is rejected for the differentiated beta series. Consequently, the test statistics indicate that the beta series is integrated of order one ($I(1)$), justifying its inclusion in the analysis by differentiating the variables. The time series section reports the results of the unit root tests for the corporate governance index, market returns, trading volumes, and market volatility series. The null hypothesis of non-stationarity is decisively rejected for both unit root tests applied to market returns and market volatility series. However, for the corporate governance index and trading volume of Borsa Istanbul, the hypothesis can only be rejected for the ADF unit root test with a constant specification. In summary, the joint results confirm that the corporate governance index,

Table 5

Unit root test results.

Variable	CIPS Test		CADF Test	
	C	C&T	C	C&T
RS	−5.750	−5.881	−3.317	−3.328
EXR	−5.994	−6.128	−3.614	−3.714
SZ	−2.244	−2.628	−2.048	−2.278
MB	−3.110	−3.455	−2.221	−2.451
BT	−1.035	−1.448	−1.352	−1.711
D.BT	−5.157	−5.388	−3.084	−3.310
IR_C	−5.264	−5.450	−3.009	−3.212
IR_3F	−5.263	−5.446	−3.018	−3.214
IR_4F	−5.288	−5.491	−3.025	−3.219
IR_5F	−5.270	−5.479	−3.031	−3.224
Critical Values				
10%	−2.01	−2.50	−2.01	−2.50
5%	−2.06	−2.54	−2.06	−2.54
1%	−2.14	−2.62	−2.14	−2.62

ADF with Breakpoint			Ng Perron							
			C				C&T			
	C	C&T	MZa	MZt	MSB	MPT	MZa	MZt	MSB	MPT
CRP	−7.39	−1.72	2.66	1.38	0.52	84.17	7.16	3.54	0.49	42.96
RM	−10.62	−9.32	−25.64	−3.58	0.14	3.57	−25.92	−3.56	0.14	1.06
VLt	−9.69	−7.72	−21.47	−3.24	0.15	4.48	−20.98	−3.24	0.15	1.18
VLM	−0.38	−3.50	1.27	0.74	0.58	29.15	−6.70	−1.73	0.26	13.66
Critical Values										
1%	−5.72	−4.95	−23.80	−3.42	0.14	4.03	−13.80	−2.58	0.17	1.78
5%	−5.18	−4.44	−17.30	−2.91	0.17	5.48	−8.10	−1.98	0.23	3.17
10%	−4.89	−4.19	−14.20	−2.62	0.19	6.67	−5.70	−1.62	0.28	4.45

*C is the model specification with constant and trend, while C&T is the model specification with constant only.

* The null hypothesis is “the variable is not stationary” for all unit root tests used in the table, including both panel unit root test and time series unit root test.

market volatility, and market return series exhibit zero-order stationarity (I(0)), while the trading volume of Borsa Istanbul is integrated of order one (I(1)).

Cross-sectional analyses provide valuable initial insights into the risk–return relationship; however, their inherent limitations require more sophisticated approaches to fully capture the dynamic complexity. This study overcomes the limitations of static cross-sectional analyses by employing a dynamic panel data estimation technique. This technique allows for a deeper examination to uncover the multifaceted effects of risk on individual stock returns over time. Dynamically modeling the evolving nature of the relationship provides a nuanced understanding of how different risk factors affect expected returns over different time horizons. Stock returns are a function of several indicators, such as beta, market returns, and company size, in addition to past returns. Thus, investors may be more willing to invest in stocks with steady returns. The use of one or more lagged dependent variable values as an explanatory variable in a regression model leads to several estimation problems. In a regression model, the explanatory variables must be non-probabilistic and the covariance between the explanatory variables and error term should be zero. If the lagged dependent variable were included in the model as an explanatory variable, this assumption would not be met because of its inherent structure, as the presence of lagged dependent variables leads to correlation with unobservable panel-level effects, making standard estimators inconsistent and consequently affecting the validity of significance tests for coefficients. Arellano and Bond (1991) addressed this challenge by formulating a consistent generalized method of moments (GMM) estimator. This estimator first incorporates differencing to eliminate panel effects and uses instruments to construct moment terms. However, Blundell and Bond (1998) identified a limitation of the Arellano-Bond estimator. Specifically, they showed that the effectiveness of lagged instruments in this estimator declines as the autoregressive process becomes more persistent, which is associated with an escalation in the ratio of the variance of panel effects to the variance of idiosyncratic errors. To overcome this obstacle,

building on the contributions of Arellano and Bover (1995), Blundell and Bond (1998) propose a system estimator. This novel approach incorporates moment conditions in which lagged differences serve as instruments for the level equation and complements traditional moment conditions that use lagged levels as instruments for the difference equation. Consequently, while a static regression model with non-stochastic or lagged explanatory variables satisfies these assumptions, an autoregressive model requires the use of a dynamic estimation procedure to obtain unbiased coefficients and perform valid significance tests on the coefficients. As stock returns are a function of past realization, a dynamic panel data estimation procedure must be used to establish the relationship between idiosyncratic risk, market volatility, and individual stock returns. In this context, the Arellano-Bover/Blundell-Bond dynamic panel regression model is used to estimate the coefficients.

Table 6 lists the estimated coefficients of the Arellano-Bover/Blundell-Bond regression models. In all models, individual stock returns are the dependent variable, whereas idiosyncratic risk and market volatility obtained from the EGARCH model serve as the primary independent variables. Several additional factors, including firm size, beta, book-to-market ratio, market volatility, trading volume, and corporate governance index, are included as control variables to explain the relationship between risk and returns. Excess returns are used as the estimation thresholds to comprehensively examine the interaction between stock returns, idiosyncratic risk, and market risk (represented by market volatility). This approach allows for both positive and negative excess returns and encompasses scenarios in which stock returns either outperform or underperform the market. Consequently, three models are estimated to capture potential fluctuations in the risk–return relationship as a function of market performance: (M1) in which the stock outperforms the market, (M2) in which the market outperforms the stock, and (M3) which includes all observations. Estimating these three regression models reveals whether the relationship between idiosyncratic risk, market risk, and returns varies under different market

Table 6
Arellano-Bover/Blundell-Bond dynamic panel regression models with EGARCH based market volatility.

Variable	IR_C Model			IR_3F Model		
	M1	M2	M3	M1	M2	M3
L1.RS	−0.0873***	−0.1459***	−0.0793***	−0.0853***	−0.1476***	−0.0818***
L2.RS	−0.0282**	−0.0989**	−0.0344**	−0.0235***	−0.0126***	−0.0345***
IR	0.3338***	0.1952***	0.2611***	0.3414***	0.2059***	0.2688***
VLT_EGARCH	−0.0126**	−0.0106***	−0.0179***	−0.0132***	−0.0110***	−0.0182***
SZ	0.2178***	0.1577***	0.2036***	0.2137***	0.1511***	0.1983***
BT	−0.8515***	−0.8564***	−0.8882***	−0.8398***	−0.5430***	−0.8733***
MB	0.4538***	0.2901***	0.3252***	0.4496***	0.2875***	0.3236***
CRP	−0.4748***	−0.3649***	−0.3907***	−0.4660***	−0.3553***	−0.3804***
RM	0.7421***	0.4723***	0.6665***	0.7338***	0.4746***	0.6594***
VLM	0.0223	0.0940***	0.0836***	0.0283	0.0969***	0.0883***
Constant	−1.6998 ***	−1.099***	−1.9065***	−1.0217***	−1.6238***	−1.8540***
Variable	IR_4F Model			IR_5F Model		
	M1	M2	M3	M1	M2	M3
L1.RS	−0.0841***	−0.1470***	−0.0811***	−0.0853***	−0.1471***	−0.0812***
L2.RS	−0.0230	−0.0990***	−0.0340***	−0.0240	−0.0996***	−0.0346***
IR	0.3409***	0.2035***	0.2675***	0.3420***	0.2026***	0.2672***
VLT_EGARCH	−0.0129**	−0.0109**	−0.0180***	−0.0136***	−0.0110***	−0.0184***
SZ	0.2142***	0.1519***	0.1989***	0.2142***	0.1513***	0.1983***
BT	−0.8409***	−0.5419***	−0.8718***	−0.8328***	−0.5427***	−0.8708***
MB	0.4509***	0.2875***	0.3238***	0.4506***	0.2884***	0.3247***
CRP	−0.4675***	−0.3559***	−0.3811***	−0.4676***	−0.3555***	−0.3807***
RM	0.7322***	0.4737***	0.6579***	0.7305***	0.4709***	0.6564***
VLM	0.0272***	0.0963***	0.0876***	0.0293***	0.0983***	0.0898***
Constant	−1.6602***	−1.0318***	−1.8573***	−1.6513***	−1.0205***	−1.8434***

(***), (**), and (*) represent the significance level at %1, 5%, and 10%, respectively. L1. and L2. are lag operators. The dependent variable in all models is the individual stock return. M1 models represent the estimated regression models when excess returns are positive, M2 models represent the estimated regression model when excess returns are negative, and M3 models are estimated using all observations. IR_C, IR_3, IR_4, and IR_5 are the measures of idiosyncratic risk obtained from the CAPM, three-factor model, four-factor model, and five-factor model, respectively.

conditions.

In the first regression model, the explanatory variable representing idiosyncratic risk is derived from the CAPM. Two lags of the dependent variable are included in the model as explanatory variables. The results indicate that all M1 variables have statistically significant effects on stock returns. Idiosyncratic risk, firm size, book-to-market ratio, traded volume of Borsa Istanbul, and market returns have positive effects on individual stock returns, while the stock beta and market volatility obtained from the EGARCH model and Istanbul Stock Exchange Company Index have negative effects on returns. Similar results are obtained when the measure of idiosyncratic risk is changed. For M1, in which stock returns exceed market returns, the estimated coefficients and their signs are consistent for four different measures of risk. In all models, idiosyncratic risk and market volatility have statistically significant effects on returns, while idiosyncratic risk has a positive effect on returns, and market risk has a negative effect on returns. Accordingly, a 1% increase in idiosyncratic risk increases stock returns by approximately 0.3395% on average. Based on the four models, the effect of market risk is very limited compared with that of idiosyncratic risk. On average, a 1% increase in market risk reduces stock returns by approximately 0.01331%. Consequently, idiosyncratic risk and market volatility have positive and negative effects, respectively, on stock returns in the case of positive excess returns.

The second scenario occurs when market returns outperform stock returns. All the variables in M2 have statistically significant effects on stock returns, except for the two lagged values of the dependent variable in the models that include IR_3F and IR_4F as risk measures. The signs of the coefficients in these models are consistent with those in both M2 and M1. Accordingly, idiosyncratic risk, market returns, firm size, trading volume, and book-to-market ratio have positive effects on returns during periods of negative excess returns. Market volatility negatively affects stock returns, when both negative and positive excess returns occur. A 1% increase in idiosyncratic risk increases stock returns by approximately 0.2018%, on average. The impact of market risk was

very limited compared with idiosyncratic risk, as in M1. A 1% increase in market risk reduces stock returns by approximately 0.0108% on average. In the third specification, the regression models were estimated using the full dataset. In this case, we determine the impact of idiosyncratic risk and market volatility on stock returns for periods in which excess returns can be both positive and negative. The coefficients are statistically significant and consistent with the previous two model specifications. The coefficient of the idiosyncratic risk variable is calculated to have a positive value of approximately 0.2662% for M3, and the average market risk coefficient is estimated to be -0.018% . Thus, including the control variables, the effects of idiosyncratic risk and market volatility on stocks are consistent across models. Only the magnitudes of the coefficients differed across the models. Accordingly, the coefficient of the idiosyncratic risk variable is highest when excess returns are positive, while the magnitude of the coefficient is lowest when excess returns are negative.

The ARCH/GARCH models and their specifications are widely used in financial studies to compute volatility series. In this context, the EGARCH model is frequently used in the financial literature. The choice of a method to calculate the volatility of a financial series is of secondary importance, as no definitive proof supports the superiority of one technique over another. Nevertheless, these methods can be used to check the robustness. The estimated coefficients likely remain robust regardless of the method used to calculate volatility as long as the relationship between the variables remains consistent across the estimated models. This study aims to provide a robust and comprehensive understanding of risk that includes both market- and firm-specific components; thus, the EGARCH model is preferred in addition to the GARCH model. Table 6 shows the coefficients of the regressions with the volatility series derived from the EGARCH, whereas Table 7 shows the coefficients of the regression models based on the GARCH volatility series.

Table 7 presents the estimated coefficients derived from the Arellano-Bover/Blundell-Bond dynamic panel regression models

Table 7
Arellano-Bover/Blundell-Bond dynamic panel regression models with GARCH based market volatility.

Variable	IR_C Model			IR_3F Model		
	M1	M2	M3	M1	M2	M3
L1.RS	−0.0945***	−0.1067***	−0.1684***	−0.0972***	−0.1042***	−0.1704***
L2.RS	−0.0349***	−0.0334**	−0.1078**	−0.0352***	−0.0286**	−0.1085***
IR	0.2498***	0.3258***	0.1755***	0.2590***	0.3348***	0.1853***
VLT_GARCH	−0.1232***	−0.0600***	−0.2277***	−0.1236***	−0.0620***	−0.2252***
SZ	0.2371***	0.2099***	0.2251***	0.2318***	0.2063***	0.2187***
BT	−0.7025***	−0.7063***	−0.2558***	−0.6890***	−0.6931***	−0.2424***
MB	0.3331***	0.4673***	0.3029***	0.3316***	0.4630***	0.3010***
CRP	−0.3329***	−0.4027***	−0.2344***	−0.3236***	−0.3942***	−0.2276***
RM	0.6741***	0.7621***	0.5117***	0.6681***	0.7553***	0.5115***
VLM	0.1057***	0.0393***	0.1117***	0.1092	0.0438**	0.1193***
Constant	−3.5742***	−2.3376***	−4.3686***	−3.5239***	−2.3205***	−4.2688***
Variable	IR_4F Model			IR_5F Model		
	M1	M2	M3	M1	M2	M3
L1.RS	−0.0964***	−0.1025***	−0.1699***	−0.0966***	−0.1035***	−0.1702***
L2.RS	−0.0349***	−0.0281**	−0.1082***	−0.0353***	−0.0288***	−0.1087***
IR	0.2584***	0.2069***	0.1837***	0.2587***	0.3368***	0.1837***
VLT_GARCH	−0.1239**	−0.0631**	−0.2254***	−0.1238***	−0.0623***	−0.2255***
SZ	0.2324***	0.2069***	0.2196***	0.2317***	0.2071***	0.2187***
BT	−0.6875***	−0.6925***	−0.2417***	−0.6865***	−0.6860***	−0.2420***
MB	0.3316***	0.4639***	0.3010***	0.3326***	0.4635***	0.3019***
CRP	−0.3241***	−0.3951***	−0.2282***	−0.3240***	−0.3969***	−0.2275***
RM	0.6671***	0.7547***	0.5108***	0.6656***	0.7530***	0.5085***
VLM	0.1085***	0.0429***	0.1188***	0.1100***	0.0439***	0.1204***
Constant	−3.5303***	−2.3290***	−4.2810***	−3.5128***	−2.3124***	−4.2662***

(***), (**), and (*) represent the significance level at %1, 5%, and 10%, respectively. L1. and L2. are lag operators. The dependent variable in all models is the individual stock return. M1 models represent the estimated regression models when excess returns are positive, M2 models represent the estimated regression model when excess returns are negative, and M3 models are estimated using all observations. IR_C, IR_3, IR_4, and IR_5 are the measures of idiosyncratic risk obtained from the CAPM, three-factor model, four-factor model, and five-factor model, respectively.

examining the relationship between idiosyncratic risk, market volatility, and individual stock returns, along with several control variables. These models use GARCH-derived market volatility as an independent variable. To assess the potential impact of risk on returns comprehensively, three scenarios are planned: positive stock performance (M1), negative stock performance (M2), and all observations (M3). Each model incorporates four different measures of idiosyncratic risk derived from the CAPM and factor models and uses the GARCH-derived market volatility series. This multi-layered approach ensures a robust evaluation of the risk-return relationship across different risk components and performance scenarios. The estimated coefficients are consistent with those obtained using EGARCH-derived market volatility (Table 6). Accordingly, on average, a 1% increase in idiosyncratic risk correlates with a positive return of approximately 0.2565%. Conversely, increased market volatility is associated with a negative return reaction, reflecting increased risk aversion during volatile market conditions. Furthermore, the results extend beyond idiosyncratic and market risk factors. Tables 6 and 7 consistently show that firm size, market-to-book ratio, market returns, and market trading volume are positively correlated with returns. Conversely, higher beta and corporate governance index values are associated with lower expected returns, supporting the risk and governance premium interpretations.

4. Conclusion

The traditional financial theory assumes a positive relationship between risk and returns. However, in emerging markets, characterized by less mature market dynamics and higher firm-specific risks, this relationship requires a more nuanced examination. This study aims to reveal the impact of market and idiosyncratic risks on stock returns traded on the Borsa Istanbul. The study uses a dataset of 202 stocks covering 54 quarters and follows a two-pronged approach. First, the Fama-MacBeth (1973) two-stage cross-sectional regression is used to capture the horizontal relationship between risk and return. Second, the Arellano-Bover/Blundell-Bond dynamic panel regression model is applied to examine the evolution of this relationship over time. To account for possible methodological dependencies, two different market risk measures derived from the GARCH and EGARCH models are included. In addition, four different idiosyncratic risk measures are employed derived from the CAPM and three-, four-, and five-factor models. To further explore heterogeneity, three partial regression models are established for each risk measure using excess returns as thresholds. This multifaceted approach aims to contribute to a more nuanced understanding of the risk-return relationship in the context of Borsa Istanbul, considering the unique characteristics of emerging markets and providing valuable insights for investors and policymakers.

Thus the coefficient of the Fama-MacBeth (1973) two-stage regression model confirms the positive and statistically significant role of idiosyncratic risk on returns. This result remains consistent across eight regression models using four different measures of idiosyncratic risk. Specifically, the estimated coefficients indicate that a 1% increase in idiosyncratic risk is associated with a 0.0468% increase in expected returns. Market volatility is also a statistically significant determinant of stock returns. However, the coefficients show an inverse relationship between market returns and volatility, suggesting that the susceptibility to significant losses is higher during periods marked by high rather than low volatility. In addition, market returns, firm size, stock beta, and Borsa Istanbul trading volume show remarkable significance in explaining stock returns. Among the control variables used in the Fama-MacBeth (1973) regressions, the book-to-market ratio and corporate governance index had an insignificant effect on stock returns. Furthermore, the Arellano-Bover/Blundell Bond approach reveals a statistically significant and positive relationship between idiosyncratic risk and individual stock returns. This relationship holds for both EGARCH and GARCH specifications, including all 24 estimated models. Particularly notable is the stability of the impact of idiosyncratic risk on

returns, regardless of whether stock returns outperform or underperform the market. However, market volatility has an inverse relationship with stock returns, which remains consistent across models, regardless of whether the measure of market volatility is derived from EGARCH or GARCH specifications. In addition to these main results, the control variables contribute to the dynamics of returns. In particular, the corporate governance index and beta have negative effects on stock returns, whereas positive relationships are found between stock returns and book-to-market ratio, firm size, Borsa Istanbul trading volume, and market returns. Notably, the regression coefficients derived from the cross-sectional and panel data regressions show remarkable consistency across the different measures of idiosyncratic risk, with minimal variability in coefficient magnitude.

Declaration of competing interest

There are no conflicts of interest or disagreements between the authors regarding the content or authorship of this manuscript.

CRediT authorship contribution statement

Salih Çam: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition, All authors have reviewed and approved the final version of the manuscript. **Önder Uzkaralar:** Conceptualization, Methodology, Validation, Investigation, Resources, Data curation, Writing – review & editing, Visualization, Supervision, Project administration, Funding acquisition, All authors have reviewed and approved the final version of the manuscript. **Metin Borak:** Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Project administration, Funding acquisition, All authors have reviewed and approved the final version of the manuscript.

References

- Ali, S. R. M., Hasan, M. N., & Östermark, R. (2020). Are idiosyncratic risk and extreme positive return priced in the Indian equity market? *International Review of Economics & Finance*, 70, 530–545.
- Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1), 259–299.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277–297.
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29–51.
- Au, A. S., Doukas, J. A., & Onayev, Z. (2009). Daily short interest, idiosyncratic risk, and stock returns. *Journal of Financial Markets*, 12(2), 290–316.
- Bali, T. G., & Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial and Quantitative Analysis*, 43(1), 29–58.
- Bali, T. G., Cakici, N., Yan, X., & Zhang, Z. (2005). Does idiosyncratic risk really matter? *The Journal of Finance*, 60(2), 905–929.
- Baltagi, B. H. (1998). Panel data methods. In *Handbook of applied economic statistics* (pp. 311–323). Boca Raton: CRC Press.
- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3–18.
- Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. *The Journal of Finance*, 32(3), 663–682.
- Beja, A. (1972). On systematic and unsystematic components of financial risk. *The Journal of Finance*, 27(1), 37–45.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115–143.
- Bowman, R. G. (1979). The theoretical relationship between systematic risk and financial (accounting) variables. *The Journal of Finance*, 34(3), 617–630.
- Bozhkov, S., Lee, H., Sivarajah, U., Despoudi, S., & Nandy, M. (2020). Idiosyncratic risk and the cross-section of stock returns: The role of mean-reverting idiosyncratic volatility. *Annals of Operations Research*, 294, 419–452.
- Brown, D. P., & Ferreira, M. A. (2016). Idiosyncratic volatility of small public firms and entrepreneurial risk. *Quarterly Journal of Forestry*, 6(1), Article 1650002.
- Campbell, J. Y. (1987). Stock returns and the term structure. *Journal of Financial Economics*, 18(2), 373–399.
- Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57–82.

- Chabi-Yo, F. (2011). Explaining the idiosyncratic volatility puzzle using stochastic discount factors. *Journal of Banking & Finance*, 35(8), 1971–1983.
- Chan, L. K., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and stock returns in Japan. *The Journal of Finance*, 46(5), 1739–1764.
- Chen, S. S. (2012). Revisiting the empirical linkages between stock returns and trading volume. *Journal of Banking & Finance*, 36(6), 1781–1788.
- Chen, Z., & Petkova, R. (2012). Does idiosyncratic volatility proxy for risk exposure? *Review of Financial Studies*, 25(9), 2745–2787.
- Chou, R. Y. (1988). Volatility persistence and stock valuations: Some empirical evidence using GARCH. *Journal of Applied Econometrics*, 279–294.
- Chua, C. T., Goh, J., & Zhang, Z. (2010). Expected volatility, unexpected volatility, and the cross-section of stock returns. *Journal of Financial Research*, 33(2), 103–123.
- Chung, K. H., & Chuwongnanant, C. (2018). Market volatility and stock returns: The role of liquidity providers. *Journal of Financial Markets*, 37, 17–34.
- Cordeiro da Cunha Araújo, R., & André Veras Machado, M. (2018). Book-to-market ratio, return on equity and Brazilian stock returns. *RAUSP Management Journal*, 53(3), 324–344.
- Cremers, K. M., & Nair, V. B. (2005). Governance mechanisms and equity prices. *The Journal of Finance*, 60(6), 2859–2894.
- Drew, M. (2003). Beta, firm size, book-to-market equity and stock returns. *Journal of the Asia Pacific Economy*, 8(3), 354–379.
- Durnev, A., Morck, R., Yeung, B., & Zarowin, P. (2003). Does greater firm-specific return variation mean more or less informed stock pricing? *Journal of Accounting Research*, 41(5), 797–836.
- Fabozzi, F. J., Kolm, P. N., Pachamanova, D. A., & Focardi, S. M. (2007). *Robust portfolio optimization and management*. John Wiley & Sons.
- Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427–465.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56.
- Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22.
- Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607–636.
- Fazil, G., & İpek, A. (2013). Does idiosyncratic volatility matter in the emerging markets? Istanbul stock Exchange evidence. *Economic Research-Ekonomska Istraživanja*, 26(3), 133–150.
- Ferreira, M. A., & Laux, P. A. (2007). Corporate governance, idiosyncratic risk, and information flow. *The Journal of Finance*, 62(2), 951–989.
- Fink, J. D., Fink, K. E., & He, H. (2012). Expected idiosyncratic volatility measures and expected returns. *Financial Management*, 41(3), 519–553.
- Fletcher, J. (2000). On the conditional relationship between beta and return in international stock returns. *International Review of Financial Analysis*, 9(3), 235–245.
- French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of Financial Economics*, 19(1), 3–29.
- Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, 91, 24–37.
- Gençay, R., Selçuk, F., & Whitcher, B. (2005). Multiscale systematic risk. *Journal of International Money and Finance*, 24(1), 55–70.
- Glosten, L. R., Jagannathan, R., & 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), 1779–1801.
- Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate governance and equity prices. *Quarterly Journal of Economics*, 118(1), 107–156.
- Goyal, A., & Santa-Clara, P. (2003). Idiosyncratic risk matters. *The Journal of Finance*, 58(3), 975–1007.
- Gu, M., Kang, W., & Xu, B. (2018). Limits of arbitrage and idiosyncratic volatility: Evidence from China stock market. *Journal of Banking & Finance*, 86, 240–258.
- Heston, S. L., Rouwenhorst, K. G., & Wessels, R. E. (1999). The role of beta and size in the cross-section of European stock returns. *European Financial Management*, 5(1), 9–27.
- Hong, G., & Sarkar, S. (2007). Equity systematic risk (beta) and its determinants. *Contemporary Accounting Research*, 24(2), 423–466.
- Huang, W., Liu, Q., Rhee, S. G., & Zhang, L. (2010). Return reversals, idiosyncratic risk, and expected returns. *Review of Financial Studies*, 23(1), 147–168.
- Hur, J., Pettengill, G., & Singh, V. (2014). Market states and the risk-based explanation of the size premium. *Journal of Empirical Finance*, 28, 139–150.
- Iqbal, M. J., & Shah, S. Z. A. (2012). Determinants of systematic risk. *The Journal of Commerce*, 4(1), 47.
- Irshad, H. (2017). Relationship among political instability, stock market returns and stock market volatility. *Studies in Business and Economics*, 12(2), 70–99.
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1), 65–91.
- Khovansky, S., & Zhylyevskyy, O. (2013). Impact of idiosyncratic volatility on stock returns: A cross-sectional study. *Journal of Banking & Finance*, 37(8), 3064–3075.
- Lee, C. F., & Rui, O. M. (2000). Does trading volume contain information to predict stock returns? Evidence from China's stock markets. *Review of Quantitative Finance and Accounting*, 14, 341–360.
- Li, Q., Bai, Y., Yan, X., & Zhang, W. (2019). Portfolio selection with the effect of systematic risk diversification: Formulation and accelerated gradient algorithm. *Optimization Methods and Software*, 34(3), 612–633.
- Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47(1), 13–37.
- Liu, Y. (2022). The short-run and long-run components of idiosyncratic volatility and stock returns. *Management Science*, 68(2), 1573–1589.
- Long, H., Jiang, Y., & Zhu, Y. (2018). Idiosyncratic tail risk and expected stock returns: Evidence from the Chinese stock markets. *Finance Research Letters*, 24, 129–136.
- Long, H., Zaremba, A., & Jiang, Y. (2020). Price nonsynchronicity, idiosyncratic risk, and expected stock returns in China. *Economic Research-Ekonomska Istraživanja*, 33(1), 160–181.
- Ma, R., Anderson, H. D., & Marshall, B. R. (2018). Market volatility, liquidity shocks, and stock returns: Worldwide evidence. *Pacific-Basin Finance Journal*, 49, 164–199.
- Malkiel, B. G., & Xu, Y. (1997). Risk and return revisited. *Journal of Portfolio Management*, 23(3), 9.
- Malkiel, B. G., & Xu, Y. (2004). Idiosyncratic Risk and security returns. *AFA 2001 New Orleans meetings*. <https://doi.org/10.2139/ssrn.255303>. <http://ssrn.com/abstract=255303>
- Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91.
- Mazumdar, K., Zhang, D., & Guo, Y. (2020). Portfolio selection and unsystematic risk optimisation using swarm intelligence. *Journal of Banking and Financial Technology*, 4, 1–14.
- Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica: Journal of the Econometric Society*, 867–887.
- Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics*, 8, 323–361.
- Morck, R., Yeung, B., & Yu, W. (2000). The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, 58(1–2), 215–260.
- Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 347–370.
- Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2), 265–312.
- Pindyck, R. S. (1984). Risk, inflation, and the stock market. *The American Economic Review*, 74, 335–351.
- Pontiff, J., & Schall, L. D. (1998). Book-to-market ratios as predictors of market returns. *Journal of Financial Economics*, 49(2), 141–160.
- Qadan, M., Kliger, D., & Chen, N. (2019). Idiosyncratic volatility, the VIX and stock returns. *The North American Journal of Economics and Finance*, 47, 431–441.
- Reeb, D. M., Kwok, C. C., & Baek, H. Y. (1998). Systematic risk of the multinational corporation. *Journal of International Business Studies*, 29, 263–279.
- Rowe, T., & Kim, J. (2010). Analyzing the relationship between systematic risk and financial variables in the casino industry. *UNLV Gaming Research and Review Journal*, 14(2).
- Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance*, 44(5), 1115–1153.
- Scruggs, J. T. (1998). Resolving the puzzling intertemporal relation between the market risk premium and conditional market variance: A two-factor approach. *The Journal of Finance*, 53(2), 575–603.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425–442.
- Shi, Y., Liu, W. M., & Ho, K. Y. (2016). Public news arrival and the idiosyncratic volatility puzzle. *Journal of Empirical Finance*, 37, 159–172.
- Silva, T. C., da Silva, M. A., & Tabak, B. M. (2017). Systemic risk in financial systems: A feedback approach. *Journal of Economic Behavior & Organization*, 144, 97–120.
- Spiegel, M. I., & Wang, X. (2005). Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk. *Yale ICF Working Paper No 05-13; EFA 2005 Moscow Meetings*. Paper <http://ssrn.com/abstract=709781>.
- Turner, C. M., Startz, R., & Nelson, C. R. (1989). A Markov model of heteroskedasticity, risk, and learning in the stock market. *Journal of Financial Economics*, 25(1), 3–22.
- Whitelaw, R. F. (1994). Time variations and covariations in the expectation and volatility of stock market returns. *The Journal of Finance*, 49(2), 515–541.
- Yang, H. F., Liu, C. L., & Chou, R. Y. (2020). Bank diversification and systemic risk. *The Quarterly Review of Economics and Finance*, 77, 311–326.
- Zaimovic, A., Omanovic, A., & Arnaut-Berilo, A. (2021). How many stocks are sufficient for equity portfolio diversification? A review of the literature. *Journal of Risk and Financial Management*, 14(11), 551.