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Araştırma Makalesi

Does Idiosyncratic Risk Have a Significant Impact on Return Probability? A Case Study of Borsa Istanbul 100 Stocks

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Abstract
Most asset pricing models ignore idiosyncratic risk, or firm-specific risk, while it is one of the most critical determinants of asset pricing and stock returns. In this paper, we investigate the impact of idiosyncratic risk on the returns of stocks traded on the Borsa Istanbul using six different fixed effect panel tobit and four different fixed effect panel logit regression models. The results of logit models suggest that as idiosyncratic risk increases, probability of positive stock returns also increases. Furthermore, an increase in a stock's market sensitivity has a negative effect on the probability of positive returns, while an increase in the market-to-book ratio, firm size, and market return has positive effects on returns. In all models, the explanatory variables, including idiosyncratic risk, market-to-book ratio, firm size, and market return, have a positive effect on returns, except for the model where negative values of dependent variable are censored at zero.

Keywords: Idiosyncratic risk, tobit model, logit model, BIST100
Jel Classification Codes: C01, C34, G12, G17

Firmaya Riskinin Getiri Olasılıkları Üzerinde Bir Etkisi Var Mı? Borsa İstanbul 100 Hisse Senetleri Üzerine Bir Çalışma

Öz
Çoğu finansal varlık fiyatlama modeli varlık fiyatlamasındaki en önemli belirleyicilerinden biri olmasına rağmen firmaya özgü riski göz ardı etmektedir. Bu çalışmada, Sermaye Varlıkları Fiyatlama Modeli kullanılarak elde edilen firmaya özgü riskin İstanbul Menkul Kıymetler Borsası'nda işlem hisse senetlerinin getirileri üzerindeki etkisi altı farklı sabit etkiler tobit regresyon modeli ve dört farklı sabit etkiler logit regresyon modeli kullanılarak araştırılmıştır. Logit modellerden elde edilen sonuçlar firmaya özgü risk arttıkça pozitif hisse senedi getirisi olasılığının da arttığını göstermektedir. Ayrıca, bir hisse senedinin piyasa duyarlılığındaki bir artış pozitif getiri olasılığı üzerinde negatif bir etkiye sahipken, piyasa-defter değeri oranı, firma büyüklüğü ve piyasa getirisindeki artış getiriler üzerinde pozitif etkilere sahiptir. Sıfırda sansürlenen model hariç, tahmin edilen tobit modellerinin tümünde firmaya özgü risk, piyasa-defter değeri oranı, firma büyüklüğü ve piyasa getirisi hisse senedi getirileri üzerinde pozitif bir etkiye sahiptir.

Anahtar Kelimeler: Firmaya özgü risk, tobit model, logit model, BİST100
JEL Sınıflandırma Kodları: C01, C34, G12, G17

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1. Introduction

The relationship between risk and expected return is a fundamental concern of modern portfolio theory. When investing in the capital markets, investors face a variety of risk factors, which can be broadly divided into two groups: systematic risk and unsystematic risk, the latter also referred to as idiosyncratic risk. Systematic risk is market-based and cannot be reduced through diversification, while unsystematic risk is company-specific and can be reduced through appropriate asset allocation (Maiti, 2019). So, the question of whether idiosyncratic risk needs to be included in asset pricing has been discussed in the many studies. Since many asset pricing models, including the Capital Asset Pricing Model (CAPM), assume that firm-specific risk can be eliminated through diversification, idiosyncratic risk is not included in asset pricing (Hyung and Vries, 2005; Huang, Liu, Rhee, and Zhang, 2010; Bozhkov, Lee, Sivarajah, Despoudi, and Nandy, 2020). However, asset prices are affected by both systematic and unsystematic risk or in other words idiosyncratic risk. The point is to determine how and to what extent idiosyncratic risk affects asset returns. The impact of idiosyncratic risk on returns depends on the market structure within developing or industrialized countries. In emerging markets, idiosyncratic risk can have a greater impact on share prices and subsequently returns than in developed markets due to inherent market imperfections. These imperfections make it difficult to construct fully diversified portfolios due to factors such as market failures, budget constraints, etc. In addition, modern portfolio theory does not provide precise guidance on the number of assets required for adequate diversification. According to some studies (Statman, 1987; Bradfield and Munro, 2017), portfolios consisting of 10 to 20 assets are well diversified, while in some studies this number is as high as fifty. Therefore, the constructed portfolios cannot fully eliminate idiosyncratic risk, and neglecting it in investment decision-making may lead to losses (Merton, 1987; Malkiel and Xu, 2002).

Asset pricing models, such as the one developed by Merton (1987), postulate a positive correlation between expected return and risk. These models assume that investors expect higher returns that correspond to the risk taken in the investment process (León, Nave and Rubio, 2007; Koluku, Pangemanan, and Tumewu, 2015). However, empirical results on the impact of risk on returns are assorted in the existing literature (Fu 2009; Qadan, Kliger, and Chen, 2019; Umutlu, 2019; Büberkökü, 2021; Yılmaz and Kale, 2022). The impact of idiosyncratic risk on expected stock returns remains controversial in the academic literature. Some studies find a positive relationship, suggesting that an increase in idiosyncratic risk is associated with an increase in expected returns (Levy, 1978; Merton, 1987). In contrast, other studies (Chung, Wang and Wu, 2019) find an inverse relationship, suggesting that stocks with higher idiosyncratic risk have lower expected returns. Finally, another study finds no statistically significant relationship between idiosyncratic risk and average expected return (Baker and Wurgler, 2006; Umutlu, 2015). There can be many reasons why consistent results cannot be obtained between idiosyncratic risk and expected returns, and they can come from both the market structure and the firm.

Several factors, including the structure of the capital market, the time horizon chosen, the data frequency used, and the measurement of the idiosyncratic risk proxy, can potentially influence the observed relationship between expected return and risk (Bali and Cakici, 2008; Chua, Goh, and Zhang, 2010; Fu, 2009; Ang, Hodrick, Xing, and Zhang, 2009; Liu, 2022). Among others, market structure has a special significance for this relationship. The impact of both systematic and unsystematic risks persists in developed markets, while the problem is more complex in developing markets due to market imperfections. Compared to developed markets, developing markets have relatively higher volatility and lower correlation between market and stock returns (De Santis and Imrohoğlu, 1997). Therefore, it may be difficult to expose uncover the role of idiosyncratic risk in asset prices for those markets where the correlation between stock returns and volatility of securities is high.

In this study, we examine the impact of idiosyncratic risk on stock returns using fixed effect panel tobit and logit regression models. Unlike cross-sectional analysis, we calculate idiosyncratic risk over twenty-four months using the CAPM model. Calculating the risk for two years provided us the opportunity to analyze a longer period of time, rather than examining the impact of idiosyncratic risk on returns based on a single observation. The CAPM model has been widely utilized to calculate idiosyncratic risk. The model assumes only market returns when pricing stocks and ignores idiosyncratic risk. Therefore, when stock returns are regressed on market returns, the error terms represent the simple fluctuations in stock returns where market fluctuations are excluded. Thus, the error terms of the CAPM model represent stock-related risks that are subtracted from the market risk with respect to each individual stock. As a result, we apply an extended and comprehensive methodology based on tobit and logit models to investigate the relationship between idiosyncratic risk and returns, enriching the existing literature in this area. The methods employed allow for an asymmetric study of risk and return dynamics. In particular, the asymmetric effects of idiosyncratic risk and return are examined within the tobit models by truncating negative and positive return values at zero. This truncation allows us to isolate the effects of idiosyncratic risk on stocks with negative and positive returns, as opposed to the full sample of stocks with both negative and positive returns. The analytical insights gained from this study should open new perspectives for future research.

We used daily closing prices data of the assets of 95 companies traded on the Borsa Istanbul to calculate idiosyncratic risk, but it is also possible to use monthly or quarterly data, which have less noise compared to daily observations. The goal of using high frequency data instead of monthly or quarterly is to show the relationship between idiosyncratic risk and returns for a more volatile time span. The Covid-19 period is not included in the analysis because the functioning of the market is significantly affected during this period (Ali, Jiang, and Sensoy, 2021). Using a period that includes the Covid-19 pandemic in the analysis may lead to unreliable or biased results. During Covid-19 pandemic, many developed and emerging markets collapsed, and many theories could not explain the market movements. The remainder of the paper is organized as follows: In the next section, the CAPM, the tobit model, and the logit model are presented. The analysis and results are presented in the third section, and the fourth section, which contains a brief summary of the paper and discussions, concludes the paper.

2. Estimation of Idiosyncratic Risk

There is no single method or model for calculating idiosyncratic risk. All methods for determining idiosyncratic risk, such as CAPM, conditional variance models, factor models, etc., provide a proxy variable for equity-based or firm-based risk rather than observed risk, and basically neither method can be said to be superior to the other. In the analysis, we preferred to utilize CAPM model that is widely used in the literature (Huang et al., 2010; Shahzad, Fareed, Wang, and Shah, 2020).

2.1. Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) is an equilibrium asset pricing framework introduced nearly simultaneously by William Sharpe (1964) and John Lintner (1965). Widely regarded as the fundamental theory of asset pricing, the CAPM integrates market returns and the risk-free interest rate into the asset pricing mechanism. The model assumes a single risk-free asset alongside n-1 risky assets and attempts to optimize the expected return of a portfolio under various assumptions. These assumptions include investment decisions based on expected return and return volatility, investor rationality and risk aversion, uniform investment horizons for all investors, availability of a risk-free rate, unconstrained borrowing and lending at the risk-free rate, and market competition and frictions. Before the introduction of the CAPM model in detail, we need to define the systematic and unsystematic risks. While systematic risk expresses the co-movement of an asset's return with the market return, the idiosyncratic risk refers to the part that is outside of this movement. Consequently, total risk can be divided into systematic risk, measured by the covariance of an asset's return with the market return, and unsystematic risk. The CAPM model define the expected return of an asset as follows:

$$E[R_i] = R_f + \frac{[E[R_M] - R_f]}{\mathrm{var}(R_M)} \mathrm{cov}\,(R_i, R_M) \tag{1}$$

where R_i is the return of asset i, R_M is the market return, R_f is the risk-free rate, $\text{var}(R_M)$ is the variance of market return, and $\text{cov}\,(R_i, R_M)$ is the covariance between the return on asset i and the market return.

$$\text{cov}(R_i, R_M) = \frac{\sum_{t=1}^{N}(R_i - E[R_i])(R_M - E[R_M])}{N} \quad (2)$$

$$\text{var}(R_M) = \frac{\sum_{t=1}^{N}(R_M - E[R_M])(R_M - E[R_M])}{N} \quad (3)$$

Substituting equations (2) and (3) into equation (1) gives the following equation.

$$\frac{\text{cov}(R_i, R_M)}{\text{var}(R_M)} = \frac{\sum_{t=1}^{N}(R_i - E[R_i])(R_M - E[R_M])}{\sum_{t=1}^{N}(R_M - E[R_M])(R_M - E[R_M])} \quad (4)$$

This is basically the slope coefficient of a regression where the dependent variable is R_i and the independent variable is R_M and it is called as β (beta) of asset i. The term β can be calculated by estimating the linear regression of asset returns on market returns.

$$R_{it} - R_{ft} = \beta_i\left[R_{Mt} - R_{ft}\right] + \varepsilon_{it} \quad (5)$$

where β_i is the slope coefficient and represents an estimate of the term $\frac{\text{cov}(R_i, R_M)}{\text{var}(R_M)}$ in equation (1), and $\varepsilon_{it} \sim (\sigma^2, 0)$ is the error terms. The CAPM model from (1) can thus be expressed as follows:

$$E[R_i] = R_f + \beta_i\left[E[R_M] - R_f\right] \quad (6)$$

According to equation (6), The expected return on the asset would increase as the coefficient of β increases in the case of $E[R_M] \geq R_f$ (Fabozzi, Focardi, Kolm, and Pachamanova, 2007).

While the model presented in equation 5 is estimated using the ordinary least squares (OLS) method, the market effect on asset returns is excluded from the model, and ε_{it} represents only the firm-specific effect. Thus, the standard deviation of ε_{it} represents the firm-specific risk. Lastly, to determine the idiosyncratic risk for $i = (1,2, \ldots, N)$, the variance of the error terms is calculated as follows:

$$\text{VAR}_{i,t}\,(\varepsilon) = \frac{1}{N_t}\sum_{t=1}^{N_t}\,\text{VAR}\left(\varepsilon_{i,t}\right) \quad (7)$$

The obtained idiosyncratic risk series used as dependent variable of tobit and logit regression models.

2.2. The Fixed Effect Logit Model

In many economic studies, the dependent variable is discrete and is represented by a binary variable y_{it}, where the value of the y_{it} is 1 if the event occurs for individual i at time t and 0 if it does not. A logit model with fixed effect can be described as follows:

$$y_{it}^{*} = x_{it}'\beta + \mu_i + v_{it} \tag{8}$$

where $y_{it}^{*} = x_{it}'\beta + u_{it}$ and y_{it}^{*} is a latent variable created as below, β and μ_i are unknown parameters to be estimated and x_{it}' is the matrix of explanatory variables. Here,

$$\begin{aligned} y_{it} &= 1 \text{ if } y_{it}^{*} > 0 \\ &= 0 \text{ if } y_{it}^{*} \leq 0 \end{aligned}$$

The probability of $y_{it} = 1$ is below

$$\Pr\,[y_{it} = 1] = \Pr\,[y_{it}^{*} > 0] = \Pr\,[v_{it} > -x_{it}'\beta - \mu_i] = F(x_{it}'\beta + \mu_i) \tag{9}$$

Provided that the density function (F) is symmetric, equation (10) holds. This condition is true for the logistic density function (Baltagi, 1995, s.209). In the analysis, we estimated four probit models in which the dependent (latent) variables are formed by positive and negative values of excess returns and individual stock returns. In the first two models, the dependent variable is formed by the positive values of excess returns, with the dependent variable taking the value of 1(one) when excess returns are positive and 0 (zero) otherwise. In the last two models, the dependent (latent) variable takes the value of 1 when individual stock returns are positive and 0 otherwise.

2.3. The Fixed Effect Tobit Model

The tobit regression proposed by Tobin (1958) is one of the most commonly used models in the case of censored data. In some situations, researchers study a specific target phenomenon, such as negative stock returns or workers who work ten hours or more in a workday, etc. Therefore, some observations in the sample are censored at a certain value of the dependent variable. Observations of the dependent variable are treated as zero if they are less than or more than the specified value in compliance with research question of the study. In this paper, we study the impact of idiosyncratic risk and some explanatory variables such as book-to-market value, firm size, etc. on positive and negative stock returns. Therefore, for each model, we applied a censor to the dependent variables, which are excess returns in the first three models and stock returns in the last three models. The model coefficients are estimated utilizing the MLE (the maximum likelihood estimation), and it is the most appropriate estimation model for censored data. A tobit model with fixed effect can be expressed as follows:

$$y_{it}^{*} = x_{it}'\beta + \mu_i + v_{it} \tag{10}$$

here, $v_{it} \sim$ IIN $(0, \sigma_v^2)$, β is coefficient vector, and μ_i is the constant of each unit in the regression model.

$$\begin{aligned} y_{it} &= y_{it}^{*} \quad \text{if } y_{it}^{*} > \gamma \\ &= 0 \quad \text{otherwise} \end{aligned} \tag{11}$$

The parameter γ is a boundary for censoring the dependent variable. If the value of the dependent variable is greater than γ, y_{it} takes the realized value, otherwise zero. So, unlike logit model in which dependent variable take 1 or 0 values, dependent variable of tobit regression is a semi-continuous variable censored at γ.

3. Empirical Results

We postulate that idiosyncratic risk has a significantly more pronounced impact on the returns of stocks traded within emerging markets, thereby explaining the relationship between idiosyncratic risk and return. Therefore, we examine the relationship between return and idiosyncratic risk for the assets of 95 companies traded on the Borsa Istanbul. We use daily returns of stocks from January 2018 to December 2019 to calculate monthly idiosyncratic risk. The period of Covid-19 is not included in the analysis due to the deterioration of the stock market. Table 1 presents the correlation matrix and the descriptive statistics for the variables used in the analysis.

Table 1: Descriptive Statistics

Variable	***Obs.***	***Mean***	***Std. Dev.***	***Min***	***Max***
IR1	2,280	4.18	5.24	0.16	108.79
Ln(BETA)	2,280	-0.20	0.36	-1.71	0.50
Ln(B/M)	2,280	0.23	0.80	-1.61	2.75
Asset Return (R_i)	2,280	1.76	13.12	-52.27	177.88
Market Return (R_m)	2,280	0.13	6.94	-10.28	14.03
Excess Return (R_e)	2,280	-1.63	11.50	-187.14	51.55
Size(%)	2,185	1.34	13.63	-52.27	177.88

	IR1	***Ln(BETA)***	***Ln(M/B)***	***Size%***	***R_m***	***R_i***
IR1	1	0.04	0.10	0.02	-0.10	0.20
Ln(BETA)	0.04	1	-0.25	0.01	-0.02	-0.03
Ln(M/B)	0.10	-0.25	1	0.02	-0.02	0.10
Size%	0.02	0.01	0.02	1	0.46	0.47
R_m	-0.10	-0.02	-0.02	0.46	1	0.49
R_i	0.20	-0.03	0.10	0.47	0.49	1

IR1 is the idiosyncratic risk calculated based on the CAPM model. BETA is the coefficient indicating the sensitivity of a stock to the financial market, calculated using the daily closing prices of the last 24 months. The B/M is the ratio of book-to-market value. R_i is monthly stock returns based on closing prices. Size represents the total market value of a company and is used as the monthly percentage change in the analysis. Finally, R_e is excess returns calculates as difference between market returns and stock returns. The dependent variables obtained from excess returns used as dependent variable of the tobit model and the Logistic regression models. However, unit root tests must be performed for all variables including dependent variables before using them in the regression models. Cross-sectional dependence is the first stage of unit root examination because it is important for performing the unit root test. In the presence of cross-sectional dependence, the second generation unit root tests must be used to examine the unit root of the variable, while the first generation tests must be used to survey the unit root of the variable in the absence of cross-sectional dependence. Table 2 shows the statistics of the Breusch-Pagan LM test and the Pesaran scaled LM test for examining the cross-sectional dependence of the variables.

Table 2: Cross-Section Dependence Test

Variables	***Breusch-Pagan LM Test Stat.***	***Pesaran scaled LM Test Stat.***	***Prob.***
IR1	10644.45	65.39	0.0000
Ln(BETA)	41595.94	392.93	0.0000
Ln(B/M)	32965.77	301.60	0.0000
R_i	17394.10	136.82	0.0000
R_m	107160	1086.74	0.0000
R_e	6984.27	26.66	0.0000
Size(%)	16271.55	124.94	0.0000
*The null hypothesis for both tests is "No cross-sectional dependence".			

The test results show that all variables have cross-sectional dependence at a generally accepted level of significance. Therefore, Pesaran's Cross-Section Augmented Dickey Fuller (CADF) test was used to search the unit root of variables. Pesaran (2007) uses a basic Augmented Dickey-Fuller (ADF) regression with the average of lagged cross-sections. This method eliminates correlation between units. The results are shown in Table 3.

Table 3: Pesaran's CADF Test

Variables	***t-bar***	***Z[t-bar]***	***P-value***
IR1	-2.453	-7.167	0.0000
Ln(BETA)	-1.947	-2.082	0.0190
Ln(B/M)	-2.147	-4.094	0.0000
R_m	-2.230	-4929	0.0000
R_i	-2.346	-6.091	0.0000
Size(%)	-2.236	-4.981	0.0000
cv10: -2.01 **cv5**: -2.07 **cv1**: -2.17			
***** cv10, cv5 and cv1 represent critical values for %90, %95 and %99 confidence level respectively.			

The t-bar and Z[t-bar] statistics for all variables are greater than the critical values. Therefore, the null hypothesis that organized as the series are nonstationary is rejected for the usual significance levels. Consequently, all variables are I (0) and can be used in the tobit and logit regressions at the level. Although it is possible to use many econometric models for analysis, logit regression and tobit regression models were preferred to examine the relationship between idiosyncratic risk and return. While logit models examine the impact of firm-based risk on the probability of increasing returns, tobit models would allow a comprehensive examination of the impact of idiosyncratic risk on the occurrence of negative and positive returns, separately. To check the robustness of the coefficients, four different regressions were estimated for the logit models and 6 for the tobit models. Using different regression models will allow us to better understand the relationship between idiosyncratic risk and return in an emerging market. In the logit model, the latent (binary) variable was constructed based on excess returns and individual stock returns. The dependence variable of the first two models was constructed in terms of the value of the excess return. The excess returns were calculated as $R_{mt} - R_{it}$ for the i^{th} stock. For the logit1 and logit2 models, whose results are shown in table 4, the latent variable was organized as a binary variable; if $R_{mt} - R_{it} \geq 0$, the latent variable takes the value 1, otherwise 0. The dependent variable of last two logit models were based on the stock returns; if $R_{it} \geq 0$, the latent variable takes the value 1, otherwise 0. $R_{i(-1)}$ is excluded in the first and third models to check whether the signs of the coefficients have changed.

Table 4: The Coefficients of Logit Regression Models

Variables	Logit1	Logit2	Logit3	Logit4
IR	-0.0361	-0.0362	0.0562	0.0533
	(0.0010)	(0.0010)	(0.0000)	(0.0000)
ln(BETA)	0.0216	0.0216	-0.3259	-0.3310
	(0.8660)	(0.8660)	(0.0470)	(0.0410)
ln(M/B)	-0.2676	-0.2678	0.1844	0.1749
	(0.0000)	(0.0000)	(0.0150)	(0.0190)
Size%	-0.0601	-0.0601	0.0642	0.0640
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{R_m}$	0.0742	0.0743	0.1559	0.1571
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{R_{i(-1)}}$		0.0002		0.0078
		(0.9510)		(0.0770)

The table contains the coefficients of four logit models. The models include IR1, BETA, B/M ratio, size (%), and lagged stock returns. IR1 is the idiosyncratic risk resulting from the error terms of the CAPM model error terms. BETA is the measure of the sensitivity of stock returns to market returns and is estimated using the most recent 24-month observation. B/M is the book value at market value. $R_{i(-1)}$ is a lagged value of stock returns. The probability values of the t-test are given in parentheses.

Table 4 shows the coefficients of the logit models estimated by the maximum likelihood method. All coefficients of the first model except BETA are statistically significant and all significant coefficients except market returns have a negative sign. Since the dependent variable is calculated from excess returns, the signs of the coefficients in this model need to be interpreted carefully. The model result suggests that an increase in idiosyncratic risk would reduce the probability of a positive excess return. In other words, the increase in idiosyncratic risk reduces the probability of positive excess returns or leads to negative excess returns. Negative excess returns are only possible if stock returns remain below the market returns. Since excess returns are $R_{mt} - R_{it}$, the coefficient actually implies a positive relationship between idiosyncratic risk and individual stock returns. Moreover, the coefficient of market returns was positively estimated in the first model. Here, a 1% increase in market returns would increase the probability of having positive excess returns by 0.075%, or in other words, an increase in market returns leads to a decrease in stock returns. The market-to-book ratio and company size also had a negative impact on excess returns or a positive impact on stock returns. A lagged value of individual stock returns was added to the second logit model as an explanatory variable, in which the dependent variable (latent or binary) obtained from excess returns. But, the magnitude and the probability values of the t test were almost unchanged, and the signs of the coefficients were consistent with the first model. The lagged returns had no statistically significant effect on reducing or increasing the probability of positive excess returns.

The dependent variable of the third and fourth logit models was calculated by using individual stock returns. The model results show that idiosyncratic risk, book-to-market ratio, firm size, and market return have a positive impact on the probability of a stock generating positive returns, while stock beta has a negative and statistically significant impact. A 1% increase in idiosyncratic risk would increase the probability of a stock having positive returns by 0.0562%. Here, the sign of idiosyncratic risk became positive compared to the first two models. However, the impact of idiosyncratic risk on returns was essentially consistent because of the dependent variables used in the model. For example, the latent variable in the logit1 and logit2 models was obtained from $R_{mt} - R_{it}$, whereas in the last two models it was calculated based on R_{it}. A decrease in $R_{mt} - R_{it}$ means an increase in the R_{it}. Therefore, the signs of the coefficients had to be changed in the last two models to match the first two. Increasing the sensitivity of individual stocks to the market would reduce the probability of positive stock returns according to the beta coefficient in the third model. A lagged value of stock returns was added to the last model to check the consistency of the coefficients. The results and signs of the coefficients were almost unchanged and consistent with the coefficients of the previous model. Although the lagged values of stock returns had a statistically positive effect on current returns, the magnitude of the coefficient was close to zero. That is, the effect of prior returns on current returns was negligible.

Table 5: The Coefficients of Tobit Regression Models

	Tobit1	**Tobit2**	**Tobit3**	**Tobit4**	**Tobit5**	**Tobit6**
IR1	0.1129	-0.8682	-0.5874	-0.1164	0.9478	0.4514
	(0.0060)	(0.0000)	(0.0000)	(0.0050)	(0.0000)	(0.0000)
ln(BETA)	-0.1458	1.1991	0.7800	-1.8459	-0.5615	-0.4541
	(0.8030)	(0.1240)	(0.2160)	(0.0030)	(0.4790)	(0.4480)
ln(M/B)	-1.3766	-1.5390	-1.2118	1.1478	1.4128	1.2244
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Size%	-0.2471	-0.3073	-0.2777	0.2468	0.3044	0.2798
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{R_m}$	0.3429	0.3335	0.3023	0.7146	0.9018	0.6960
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{R_{i\,(-1)}}$	-0.0028	0.0337	0.0279	0.0193	-0.0239	-0.0181
	(0.8640)	(0.1160)	(0.1140)	(0.2570)	(0.2680)	(0.2800)
C	-0.7923	4.6291	1.6759	0.4462	-5.2480	-1.1167
	(0.0090)	(0.0000)	(0.0000)	(0.1670)	(0.0000)	(0.0000)

The table reports coefficient of six tobit models. The models contain IR1, BETA, B/M ratio, Size (%) and a lagged stock returns. IR1 is idiosyncratic risk that obtained from error terms of regression of stock returns on market returns. BETA is the measurement of sensitivity of stock's return to market return and is estimated as utilizing last 24-month observation. B/M is book to market value. is the $R_{i\,(-1)}$ a lagged values of stock returns. The probability values of t test are reported in parentheses.

Table 5 summarizes the estimation results of six tobit models with different dependent variables constructed with different censoring values. The dependent variable of the first three models was constructed using excess returns, while the dependent variable of the last three models was constructed using stock returns. The negative values of excess returns were censored to zero in the first model and the positive values of excess returns were censored to zero in the second model, while no censoring was done for the dependent variable of the third model. By implementing left censoring, right censoring, and no censoring for excess returns, we conducted a comprehensive analysis of the impact of idiosyncratic risk on returns. Therefore, the estimation results would show whether the relationship is consistent for negative returns, positive returns, and the entire sample. Furthermore, the negative values of stock returns were censored to zero in the fourth model and the positive values of stock returns were censored to zero in the fifth model, while no censoring was done in the last model.

The coefficients of tobit model show that idiosyncratic risk and market returns have a positive and statistically significant effect on returns, while the market-to-book ratio and firm size have negative effects on it. The negative excess returns in the first tobit model were censored to zero. The negative excess return occurs when the market return is higher than the stock return because the excess return, calculated as $R_{mt} - R_{it}$. The coefficient implies that a 1% increase in the idiosyncratic risk would cause $R_{mt} - R_{it}$ to increase by 0.1129. An increase in excess return is possible in two ways: an increase in market return with constant stock return or a decrease in stock return with constant market return. In both cases, idiosyncratic risk negatively affected individual returns when negative excess returns were censored to zero. The left-censored dependent variable is one side of the search for the relationship between idiosyncratic risk and return. The other is the right censoring of the dependent variable to zero, which is shown in the Table 5 as the tobit 2. In this case, the values of the dependent variable were zero or negative due to censoring on the right side of zero. According to the coefficient, a 1% increase in idiosyncratic risk would cause by 0.8682 decrease in excess return. A potential decrease in excess return can occur in two ways: Increase in stock return with constant market return or vice versa. In the third tobit model, the dependent variable was not censored. The sign and significance of idiosyncratic risk remained unchanged in this model. The effect of stock sensitivity to the market was not statistically significant in the first three models in which the dependent variable was excess return. Finally, in the first three tobit models, firm size had a negative effect and market return had a positive effect on stock returns, while a lagged value of individual return had no statistically significant effect.

The dependent variable of the fourth, fifth, and sixth tobit models were stock returns with left censoring at zero, right censoring at zero, and no censoring, respectively. To claim that the effects of idiosyncratic risk on returns are consistent across models, the signs of the coefficients of the first and fourth models must be opposite, while the coefficients of tobit2 and tobit3 models must have the opposite sign of the tobit5 and tobit6 models. The mentioned relationship for the sign of the coefficient of idiosyncratic risk was present in all models. The coefficient of idiosyncratic risk was positive in the first model, while it was negative in the fourth model. Moreover, this coefficient was negative in the third and fourth models, while it was positive in the fifth and sixth models. The effect of market return on stock returns was statistically significant in all estimated models, and the signs of the coefficients were consistent across the models. Firm size and market-to-book ratio had a negative effect on returns in the regressions where the dependent variable was $R_{mt} - R_{it}$ and had a positive effect on returns in the regression where the dependent variable was R_{it}. Overall, the results suggest that the effects of firm size and market-to-book ratio are unchanged with respect to the left or right censor of the dependent variable.

4. Conclusion

Identifying the relationship between risk and return is important in emerging markets. To identify the impact of idiosyncratic risk on stock returns, we use logit and tobit regression models. Tobit models are particularly useful because they allow us to assess the consistency of the firm-specific relationship between risk and return across different censoring points of the dependent variable. The results of both the logit and tobit models provide a comprehensive examination of the relationship between idiosyncratic risk and return. The coefficients of the logit model indicate a negative relationship between idiosyncratic risk and stock returns. In other words, an increase in firm-specific or idiosyncratic risk is associated with a lower probability of positive excess returns. This observed negative relationship between idiosyncratic risk and return can be partly attributed to the characteristics of emerging markets. Compared to developed markets, emerging markets often exhibit higher idiosyncratic risk. This can be explained by factors such as a smaller number of well-established companies and market structure imperfections. Market imperfections can lead to inefficiencies and increased speculative activity, which ultimately leads to higher systematic and unsystematic risk for companies. In the next step of the analysis, six different tobit regressions were run with different censored values derived from excess returns and stock returns. These models used zero as the reference point for the dependent variables. According to the coefficients obtained from the tobit regressions, an escalation of idiosyncratic risk leads to an increase in excess returns when excess returns are positive. Conversely, an increase in idiosyncratic risk leads to a decrease in excess returns when excess returns are negative. As a result, firm-specific or idiosyncratic risk emerges as one of the most important determinants of stock prices on the Borsa Istanbul in emerging markets. Moreover, the estimated models do not provide evidence on the impact of stock market sensitivity, except in the tobit4, logit3 and logit4 models where the dependent variable was stock returns. A negative and statistically significant coefficient is observed in these models. Finally, companies with higher market-to-book ratios are expected to have higher stock returns. Most of the BETA coefficients are estimated to be positive and statistically significant in the tobit and logit models. In addition, firm size is found to be an important determinant of stock returns. Firm size implies the institutional structure of the firm and should therefore have a positive effect on returns. This is consistent with expectations, as evidenced by the fact that the coefficient is consistently positive in all models.

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Ethics Statement: The author declares that ethical rules have been followed in all preparation processes of this study. In case of a contrary situation regarding scientific ethics issues, all responsibility belongs to the authors of the study and Çankırı Karatekin University Journal of Faculty of Economics and Administrative Sciences has no responsibility.