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THE TIME-VARYING BETA RISK OF MINING AND QUARRYING SECTOR WITH UNIVARIATE GARCH-TYPE MODELS: THE CASE OF TURKEY

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ABSTRACT

Fast changes in financial markets caused by globalization and floating exchange rate policies increase the dependency and uncertainty between markets, causing volatility which is a statistical measure of the change in the price of financial assets, to display a dynamic structure. This dynamic structure emerges as the reason for the increasing interaction and integration of international developing economies and countries with each other and the strengthening of economic relations. In this case, financial markets become more sensitive to developments and changes, making it difficult for investors to make financial decisions. This situation causes researchers and investors to focus on the concept of risk and volatility models. For this reason, in this study was conducted for the systematic risk or beta risk, which is the risk that the investors who create the risk cannot avoid, for the first time BIST National All index (BIST) and all companies belonging to mining and quarrying are used the daily frequency data on the date of last ten years which 18.11.2011-18.11.2021. For the time-varying beta risk parameters, the Conditional Capital Asset Pricing Model (C-CAPM) is used. Time-varying Linear Market Model (Tv-LMM) is a data production model consistent with C-CAPM is modeled with GARCH, EGARCH, FIGARCH and APARCH that are univariate GARCH type models. According to the findings, to the Bayesian information criterion (BIC), the Akaike's information criterion (AIC), and the Hannan-Quinn information criterion (HQC) model benchmarking criteria, it was concluded that the GARCH-type model that best models time-varying beta risk differs according to companies. For this reason, the GARCH-type models used are not superior to each other. In addition, it has been concluded that the mining and quarrying companies have the same relationship with the market, there is a leverage effect in all companies on this period and IPEKE is the riskiest investment in this portfolio.

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1. INTRODUCTION

The increasing interaction and integration of international developing economies and countries with each other and the strengthening of economic relations cause rapid changes in financial markets, the dependency, and uncertainty between markets to increase. In this case, financial markets become more sensitive to developments and changes. For this reason, investors want to know the risk-return level relationship between their investments and how their returns change over time.

The theory modeling the risk-return relationship between financial assets was first developed by Markowitz [1]. The modern portfolio theory (MPT) includes the variance-covariance model, which suggests that the risk will decrease with the diversification of financial assets in the portfolio. Based on this theory is the Capital Asset Pricing Model (CAPM), which is frequently preferred by investors due to its ease of implementation and flexibility of parameters proposed by Sharpe, Lintner and Mossin [2, 3, 4].

The CAPM includes the beta risk parameter and gives how the financial asset changes according to the market and whether the risk is high. The Linear Market Model (LMM), which is consistent with this model, summarizes beta risk with a stationary or fixed beta parameter. One of the most important assumptions of the model is the linearity between the variables in the model. It has been proven in many studies that this assumption cannot be met [5, 6, 7, 8]. Therefore, The Conditional Capital Asset Pricing Model (C-CAPM) was in which the time-varying beta parameter is used instead of the stationary or fixed beta parameter created by Jagannathan and Wang [9]. That is, the Time-varying Linear Market model (Tv-LMM), which is consistent with this model, summarizes the beta risk with the dynamic or time-varying beta parameter. In the studies given in the literature, it has been observed that GARCH-type models are frequently preferred for the time-varying beta parameter [10, 11, 12, 13, 14, 15, 16, 17].

In this paper, the first to address the systematic risk or also known as beta risk of the mining and quarrying industry. The beta risk or systematic risk measurement of the quarrying and mining sector in Turkey, which is missing in the literature, is discussed. For this purpose, a portfolio was created by taking the daily frequency data of all quarrying and mining companies in the BIST National All index covering the period 18.11.2011-18.11.2021. The Conditional Capital Asset Pricing Model (C-CAPM), which allows time-varying beta parameter, was used as the basic model. The time-varying beta parameter is modeled with GARCH, EGARCH, FIGARCH, and APARCH that are univariate GARCH type models. Additionally, features and effects on these models are described. First of all, it is aimed to guide the investors who want to invest in this sector and to summarize the different features and effects of the models at the date of research in this sector. in addition, the garch models, which are the volatility models that have become more famous in recent years, and the beta risk, which is systematic risk, have been examined for this sector, which has not been investigated before, researchers have been provided with an idea, and contribute to the literature.

2. LITERATURE REWIEW

There are two parts to the literature research. The first is the volatility models used in beta risk which changes over time, and the second is volatility studies with GARCH-type models.

Brooks et al. [13] used the ARCH model, the Kalman filter method and the Schwert and Seguin approach [18] to modeling and estimation of the time-varying beta coefficient and the data's period of 1974 to 1996 from the industry for Australian. Faff et al. [16] used the GARCH-type models, the extended market model of Schwert and Seguin approach [18] and the Kalman Filter algorithm to modeling and estimation of the time-varying beta coefficient of the daily data's period of 1 January, 1969 to 30 April, 1998 from the 32 different UK industry sectors. Brooks et al. [14] used the bivariate GARCH model, the Schwert and Seguin [18] approach, and the Kalman filter method to modeling and estimation of the time-varying beta coefficient of the weekly data's period of 1970 to 1995 from Morgan Stanley country index. Mergner and Bulla [12] used the t-GARCH (1,1) model, two different Kalman filter (KF) based approaches, Monte Carlo likelihood technique and two Markov switching models to modeling and estimation of the time-varying beta coefficient of the weekly data's period of 1987 to 2005 from the industry for 18 pan-European countries. Altinsoy [11] made Turkey Real Estate Investment Trust (REIT)'s modeling and estimation of time-varying beta in daily and weekly frequencies between 2002 to 2009 to compare Turkey with developed and developing countries with Schwert and Seguin model, DBEKK GARCH model, and the Kalman Filter. Köseoğlu and Gökbulut [15] used the period March 2001 to March 2011 for the stability of the service, finance, and industry sectors using GARCH-type models for the ISE's time-varying beta coefficient. Neslihanoğlu [17] used the Ordinary Least-Squares method (OLS), the GARCH and GJR-GARCH model, and the Kalman Filter algorithm. For the modeling and estimation of beta behavior of the weekly data covering the period of 01.08.2002 to 16.02.2012 from 19 Turkish industrial sectors in the ISE. Aksoy [10] used the GARCH, EGARCH and GJR-GARCH models. For the modeling and estimation of the time-varying beta coefficient of the weekly and daily data covering the period of 01.08.2014 to 01.08.2019 from the transportation industry for BIST.

Peters [19] made volatility estimates with GARCH, EGARCH, GJR-GARCH and APARCH models, using 15-year daily return data on FTSE 100 and DAX 30 Indices, which are considered to be two important indices in Europe. According to the result of this study, that better volatility estimates can be made with the asymmetric GARCH models, GJR-GARCH and APARCH, compared to the symmetrical GARCH models. Pan and Zhang [20] used the time series containing 1200 data, which includes 04.01.2000 to 31.12.2004, in this research in which they measured the volatility of China's two important Shanghai and Shenzhen stock markets with linear and GARCH models. According to the result of this study, GARCH stock market and APARCH models for Shanghai stocks and GJR and ARCH models for the Shenzhen stock market have better results in volatility estimation. Alberga et al. [21] compared the estimation performances of the conditional variance models with the asymmetric GJR-GARCH and APARCH models on the returns and conditional variances of asset assets seen in the Tel Aviv Stock Index (TASE). The result of this research that the most appropriate model in the volatility estimation process of the Tel Aviv Stock Index (TASE) is the EGARCH model, in which the skewed student-t distribution is used. Frimpong and Oteng-Abayie [22] investigated the volatility movements affecting the return of the Ghana Stock Market by using random walk, GARCH, EGARCH and TGARCH models with 1508-day data covering the period of 15.06.1994 to 28.04.2004. According to the findings that GARCH (1,1) is the most suitable model in estimating the volatility of the said market. Sevüktekin and Nargeleçekenler [23] used ARMA, ARCH and GARCH models for the volatility of the ISE 100 Index daily return series. According to the results that the most suitable conditional variance model was GARCH (1,1).

3. METHOD AND MATERIAL

3.1. Financial Models

3.1.1. Capital Asset Pricing Model (CAPM)

In the finance literature, CAPM or Two-Moment CAPM is the most generally prefered model to investigate the systematic risk measure beta risk, in other words, systematic covariance risk or systematic beta, put forward by Sharpe, Lintner and Mossin [2, 3, 4]. This model is defined as equation (3). The Linear Market Model (LMM) is consistent with CAPM and is the data generation process of CAPM, is defined as equation (1). This model is based on the MPT developed by Markowitz [1]. LMM is the model that allows stable beta risk (β_{im}). It is based on the assumption that the asset returns are normally distributed and the investor's utility function is of second order, that is, the utility can only be expressed with the mean and variance measures [10]. That is why it is called a two-moment model. In the model, the mean criterion expresses the expected return, and the variance criterion expresses the risk.

$$R_{it} - R_{ft} = a_i + \beta_{im} (R_{mt} - R_{ft}) + \varepsilon_{it} \qquad i = 1, \dots, n, \quad t = 1, \dots, T \tag{1}$$

The slope of the model (β_{im}) is the beta coefficient that is defined as the beta risk of the financial asset *i*.. R_{it} is return on financial asset *i*. at time *t*.. R_{ft} is risk-free rate return at time *t*. and R_{mt} is the return on portfolio at time *t*.. Here, $R_{mt} - R_{ft}$ *is* excess return on portfolio (R_{mt}) relative to the risk free return over time *t*. and $R_{it} - R_{ft}$ *is* excess return on financial asset *i*. (R_{it}) relative to the risk-free return over time *t*.. The a_i coefficient is becomes zero when the market is active, the prices in the period of interest are not affected by past prices, and the price change is assumed to be random (random walk theory). In this case, the error terms (ε_{it}) are independent, with constant variance and same distribution, and the coefficient of a_i is assumed to be zero according to the Sharpe-Lintner-Mossin version of CAPM. In this case ε_{it}, financial asset *i*. are the residuals of $i \neq k$ for $\varepsilon_{it} \sim N(0, \sigma_i^2)$ and $j > 0$ for $E(\varepsilon_{it}\varepsilon_{i\,t+j}) = 0$ in time of *t*..

Estimation of β_{im} is, under the assumption $\varepsilon_{it} \sim N(0, \sigma^2)$, defined in equation (2).

$$\hat{\beta}_{im} = \frac{\sum_{t=1}^{T}[(R_{it}^* - \bar{R}_i^*)(R_{mt}^* - \bar{R}_m^*)]}{\sum_{t=1}^{T}[(R_{mt}^* - \bar{R}_m^*)^2]} = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{2}$$

$$R_{mt}^* = R_{mt} - R_{ft}, \qquad R_{it}^* = R_{it} - R_{ft}, \qquad \bar{R}_i^* = \frac{1}{T}\sum_{t=1}^{T} R_{it}^*, \qquad \bar{R}_m^* = \frac{1}{T}\sum_{t=1}^{T} R_{mt}^*$$

Here, R_{it}^* is the excess return on financial asset *i*. at time *t*., R_{mt}^* is the excess return on portfolio at time *t*., $\bar{R}_i^*$ is the average excess return on financial asset *i*. on the total time., $\bar{R}_m^*$ is average excess return on portfolio on the total time. $Cov(R_i, R_m)$ is the covariance between the return on financial asset *i*. and on portfolio, $Var(R_m)$ is variance on the portfolio.

CAPM is defined in equation (3).

$$E(R_i) - R_f = \beta_{im}[E(R_m) - R_f] \qquad i = 1, \dots, n \tag{3}$$

Here, R_i, R_m, R_f are return on financial asset *i*., portfolio and risk free rate, recpectively. $E(R_i)$ and $E(R_m)$ are expective return on financial asset *i*. and portfolio, respectively. $E(R_i) - R_f$ is expected excess return on financial asset *i*. relative to the risk free return. $E(R_m) - R_f$ is expected excess return on portfolio relative to the risk free return. β_{im} is investment risk and market risk of financial asset *i*..

3.1.2. Conditional Capital Asset Pricing Model (C- CAPM)

While including the constant or stable beta risk parameter (β_{im}) into the model that the CAPM, including the time-varying or dynamic beta risk parameter (β_{imt}) into the model that the Conditional Capital Asset Pricing Model (C-CAPM) [24]. The Time-varying Linear Market Model (Tv-LMM) is is consistent with C-CAPM and allows time-varying beta risk (β_{imt}).

Tv-LMM is defined in equation (4).

$$R_{it} - R_{ft} = a_i + \beta_{imt}\,(R_{mt} - R_{ft}) + \varepsilon_{it}, \qquad i = 1, \dots, n, \quad t = 1, \dots, T \tag{4}$$

In this model, beta risk (β_{imt}) is calculated based on time. β_{imt} is beta risk of financial asset *i*.. at time *t.* and defined in equation (3.6). C-CAPM is defined in equation (5).

$$E(R_{it}) - R_{ft} = \quad \beta_{imt}\left[E(R_{mt}) - R_{ft}\right] \qquad i = 1, \dots, n, \quad t = 1, \dots, T \tag{5}$$

$$\beta_{imt} = \frac{Cov(R_{it}, R_{mt})}{Var(R_{mt})} \tag{6}$$

Here, $Cov(R_{it}, R_{mt})$ is the covariance between the return on financial asset *i.* and on portfolio at time *t.*, $Var(R_{mt})$ is variance on the portfolio at time *t.* So, the variance in this model should be calculated as time varying. Where, autoregressive conditional variance is used for the time-varying variance.

3.2. Statistical Models

3.2.1. Autoregressive Conditional Variance (ARCH)

The first of these models is ARCH model, which includes the dynamic feature and changing variance of a single financial asset created by Engle [25]. In its most general form, ARCH (p) model is defined in equation (7).

$$\sigma_t^2 = \quad w + \sum_{i=1}^{p} \psi_i Y_{t-i}^2 \ , \qquad t = \min(p) + 1, \dots, n \tag{7}$$

Here, σ_t^2 gives the conditional variance, ω constant term, Y_{t-i}^2 gives the square of the errors of the model, and ψ_i gives the coefficients of the errors. For the stationarity constraint, the condition $\sum_{i=1}^{p} \psi_i < 1$ must be met.

3.2.2. Generalized Autoregressive Conditional Variance (GARCH)

GARCH model which was created in the future was created by Bollerslev [26] as an extending of the ARCH model process to express more complex volatility, volatility and structure, by transforming the autoregressive conditional variable variance model into an autoregressive moving average model. In the GARCH model, as in the ARCH model, the conditional variance in the t period is not only modeled on the square of the past values of the error terms, but also on the conditional variances in the past. GARCH (p, q) model is defined in equation (8).

$$\sigma_t^2 = \quad w + \sum_{i=1}^{p} \psi_i Y_{t-i}^2 + \sum_{j=1}^{q} \theta_j \sigma_{t-j}^2 \quad , \qquad \mathrm{t} = \min(\mathrm{p}, \mathrm{q}) + 1, \dots, \mathrm{n} \tag{8}$$

Here, $\omega > 0,\ \psi_i \geq 0$ and $\theta_j \geq 0$ constraints were defined by Nelson and Cao [26] so that the conditional variance model parameters are positive at every t. Another constraint in the model is the constraint of stationarity of covariance. For this, the condition $\sum_{i=1}^{p} \psi_i + \sum_{j=1}^{q} \theta_j < 1$ must be met [10]. The coefficient sums in the GARCH model give the persistence of volatility in the face of a shock/news. If the sum is equal to 1, the GARCH model transforms into IGARCH (the integrated generalized autoregressive conditional variance) model.

Owing to the features of financial time series like extreme kurtosis, volatility clustering, leverage effect, studies on GARCH-type models have been carried out and developed in the past and today.

3.2.3. Exponential Generalized Autoregressive Conditional Variance (EGARCH)

One of these models is EGARCH model created by Nelson [27], which models the leverage effect logarithmically. Volatility is modeled based on both the magnitude and sign of the lagged error terms. In other words, EGARCH model parameters estimation is a model that does not require positive parameter estimates of the GARCH model and performs volatility modeling regardless of the sign. The GARCH model cannot differentiate between positive and negative shocks/news affecting volatility; however, considering the leverage effect, it can be said that there are situations where volatility does not give the same response to shocks and may react asymmetrically [10]. EGARCH (p, q) model is defined in equation (9).

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{q} \psi_i \frac{|Y_{t-i}|}{\sqrt{\sigma_{t-i}^2}} + \sum_{i=1}^{q} \zeta_i \frac{Y_{t-i}}{\sqrt{\sigma_{t-i}^2}} + \sum_{j=1}^{p} \theta_j \ln(\sigma_{t-j}^2) \tag{9}$$

In this model, the standardized version of the $\frac{Y_{t-i}}{\sqrt{\sigma_{t-i}^2}}$ expression is used instead of the Y_{t-i}^2 expression used in the GARCH model. Therefore, standardization ensures that the permanence and dimensions of shocks/news are clearly revealed.

3.2.4. Fractionally Integrated Generalized Autoregressive Conditional Variance (FIGARCH)

FIGARCH model has been proposed by Baillie, Bollerslev and Mikelsen [28] to model the long memory feature of the volatility of the return series over the past price changes for the volatility cluster that causes varying variance in financial time series [29]. The FIGARCH model was created by adding the $(1 - \mathrm{L})^{\mathrm{d}} = \varepsilon_t^2 + \overline{\varepsilon_t^2}$ piecewise difference operator to the GARCH model. For the stationarity constraint, the condition $\bar{d} \in [0{,}1]$ must be met.

When the piecewise difference operator is $\bar{d} = 0$, the GARCH model is obtained, and when $\bar{d} = 1$, the IGARCH model is obtained [29]. FIGARCH model is defined in equation (10).

$$\sigma_t^2 = (w - \overline{\varepsilon_t^2}) + \sum_{i=1}^{p} \psi_i \left(Y_{t-i}^2 + \overline{\varepsilon_{t-\iota}^2}\right) + \sum_{j=1}^{q} \theta_j (\sigma_{t-j}^2 - Y_{t-j}^2) \tag{10}$$

3.2.5. Asymmetric Power ARCH (APARCH)

APARCH model was proposed by Ding, Granger, and Engle [30] for the analysis of tailed and asymmetrically distributed series. It is a model created for the transformation of the series to be realized with what power, instead of taking the absolute value or squaring used for the stationarization of the series in the ARCH model [31]. APARCH (p, q) model is defined in equation (11).

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p} \psi_i (|Y_{t-1}| - \gamma_i Y_{t-i})^{\delta} + \sum_{j=1}^{q} \theta_j \sigma_{t-j}^{\delta} \tag{11}$$

Here, σ_t^{δ} is the conditional variance, $|Y_{t-1}|$ is error terms of the past periods, ψ_i is coefficients of the error terms, σ_{t-j}^{δ} is estimates of the past periods, θ_j gives the coefficients of these estimations. γ_i is effect of asymmetry. The higher the power parameter δ in the model, the stronger the volatility's dependence on that period [31].

4. RESULT

The research data of this paper covers the dates of 18 November 2011 to 18 November 2021. In this date range, a portfolio was created by taking daily frequency data of all quarrying and mining companies in the BIST National All index. The 3-month Turkish Lira Reference Interest Rate (TRLIBOR) is preferred used and risk free rate data from *http://www.trlibor.org/veriler.aspx.*

The abbreviations of the research data are given in Table 1 and Figure 1 gives the time series plots of close price of the all quarrying and mining companies on the XUTUM.

Table 1. Names and Codes of the Country's Stocks Exchange and Mining & Quarrying Companies

Codes	Explain of Codes
XUTUM	BIST National All
ALMAD	Altınyağ Combine Inc.
IPEKE	Ipek Natural Energy Resources Research and Production Inc.
KOZAA	Koza Anatolia Metal Mining Operations Inc.
KOZAL	Koza Gold Operations Inc.
PRKME	Park Electricity Production Mining Industry and Trade Inc.

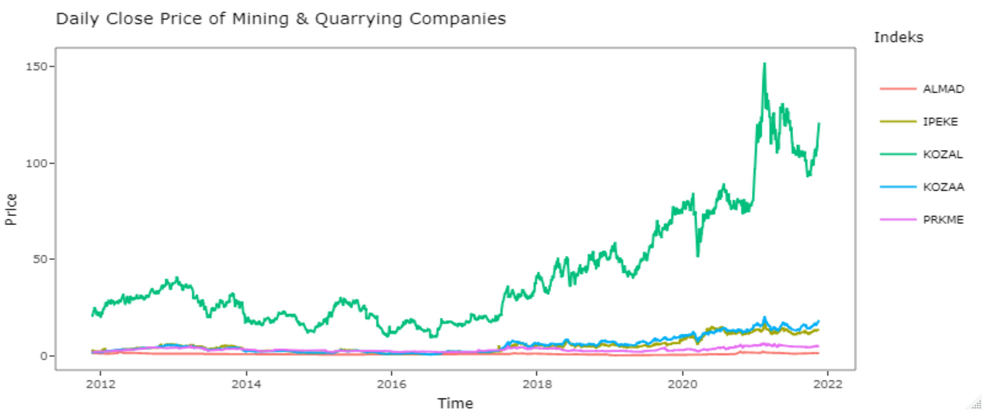


Figure 1. Close Price of the All Mining and Quarrying Companies

The daily returns for all mining and quarrying companies in the BIST National All index and the BIST National All market portfolio were obtained by the first difference of the logarithm of closing price of Turkish lira.

$$R_{it} = \ln(P_{it}) - \ln(P_{it-1}) \tag{12}$$

The three-month Turkish Interbank Offered Rate (TRLIBOR) interest rate served in percentage per annum ($TRLIBOR_t$), they can be converted to a daily rate of return as follows [12].

$$R_{ft} = \left(1 + \frac{TRLIBOR_t}{100}\right)^{\frac{1}{252}} - 1 \tag{13}$$

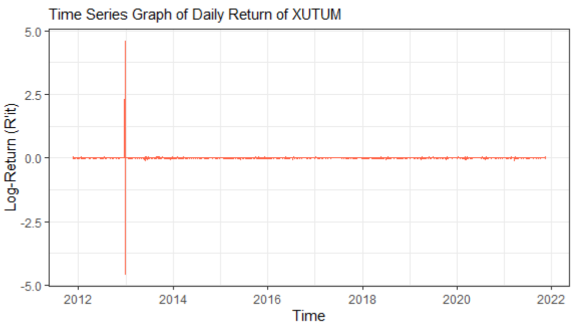
Table 2. Descriptive Statistics of Daily Returns

	Mean	Std. Dev.	Skewness	Kurtosis	JB	LB
XUTUM	0.00053	0.13053	0.18719	1226.01024	1563.9* ($p < 0.05$)	616.05* ($p < 0.05$)
ALMAD	-1.5420e-05	0.03878	0.04065	10.16816	1.0753* ($p < 0.05$)	2574.8 ($p = 0.11$)
IPEKE	0.00058	0.04357	0.95354	96.58431	9708.9* ($p < 0.05$)	34.595* ($p < 0.05$)
KOZAA	0.00085	0.03441	0.34136	5.77397	3194.8* ($p < 0.05$)	0.0008 ($p = 0.98$)
KOZAL	0.00070	0.03090	0.18010	5.53205	3514.4* ($p < 0.05$)	4281.5* ($p = 0.04$)
PRKME	0.00037	0.02678	-0.27142	8.53229	7600.8* ($p < 0.05$)	0.04200 ($p = 0.84$)
TRLIBOR	-0.99555	0.00020	1.18288	0.68853	7600.8* ($p < 0.05$)	0.04200 ($p = 0.84$)

Notes: Jarque-Bera (JB) statistic shows that the Jarque-Bera test of normality statistics; where the null hypothesis (H_0) is defined as there is no difference between the distribution of the series and the normal distribution. Jarque-Bera (JB) statistic shows that the Ljung-Box (LB) test of autocorrelation statistics; where the null hypothesis (H_0) is defined as there is no autocorrelation in the series. '*' means that null hypothesis (H_0) is rejected at 95% confidence level.

Table 2 gives descriptive statistics for the daily returns on the XUTUM market portfolio and the 5 global markets of mining and quarrying companies in the XUTUM. And this portfolio has 2509 observations. This table that the mean return on the daily XUTUM is 0.00053, with a standard deviation of about 0.13053. A positive XUTUM average indicates that investors who will invest in XUTUM during the research period will make a profit financially. The range of mean from -1.5420e-05 for ALMAD to 0.00085 for KOZAA, meaning that KOZAA generated greater financial gain on investment than ALMAD on this period. The mean return on 4 out of 5 quarrying and mining companies is more than the mean risk free rate (TRLIBOR), which stand for the minimum return an investor theoretically expects for any investment, recomming that investors would prefer to invest in these sector on this period. The highest standard deviation is that for IPEKE (0.04357), while the lowest one is that of PRKME (0.02678). For this reason, when the standart deviation is accepted as a risk measure, it can be said that the riskiest company is the IPEKE. The return distributions of all 4 company and risk-free rate (TRLIBOR), except for PRKME, show positive skewness that there are frequent small drops and a few extreme increases in returns, while negative skewness means that there are frequent small increases and a few extreme drops in returns. The range of skewness between -0.27142 (PRKME) and 1.18288 (TRLIBOR). This shows that investment experiences increases and a few extreme drops in terms of investment, while PRKME reports frequent small drops and a few extreme increases returns. The return distributions of all the quarrying and mining companies and XUTUM are leptokurtic, meaning that the market has fatter tails than the normal distribution (which has kurtosis ≥ 3) and more chance of extreme outcomes. The range of kurtosis between 1226.01024 (XUTUM) and 0.68853 (TRLIBOR). This shows that XUTUM has more chance of extreme financial losses or gains than the other investments. The normality of each investment, XUTUM and risk free rate (TRLIBOR) is also rejected at the 5% significance level using the Jarque-Bera (JB) test which is likely to be due to the substantial skewness and kurtosis observed in Table 2. To test the autocorrelation for the squared returns (proxies for volatilities) of the investment, the XUTUM and the risk free rate, the Ljung-Box (LB) test is used in this study. According to the LjungBox (LB) test, the null hypothesis of no autocorrelation for the squared returns is rejected at the 5% significance level for 4 out of the 5 companies and the XUTUM, and the risk free rate meaning that there exists a statistically significant autocorrelation for the squared returns. As results provide strong evidence for the predictability of the volatility for mining and quarrying companies, the XUTUM and the risk free rate [32]. Achieved results provide effects such as the principal features of these data are the asymmetry (left-skew and right-skew), positive mean, relatively high volatility, and leptokurtosis (fat tails) over the performance of all models while predicting the time-varying volatility. And these features match the most common features of market studies [33].

Figure 2 shows the time series graphs of returns on the XUTUM and the all mining & quarrying companies, respectively. When the graphs here are examined, It is observed that the trends in the companies and the movements of the companies over time are consistent with the comments given in Table 2. the date 2020 was defined as the COVID-19 global epidemic by the WHO was March 11, 2020, the date of the 59th presidential election in the USA was December 12, 2020, the economic crisis observed in the Turkish economy in 2018, and the effects on the markets consequently of the global economic crisis experienced in 2008-2012 effect, that is extreme fluctuations, was clearly observed.



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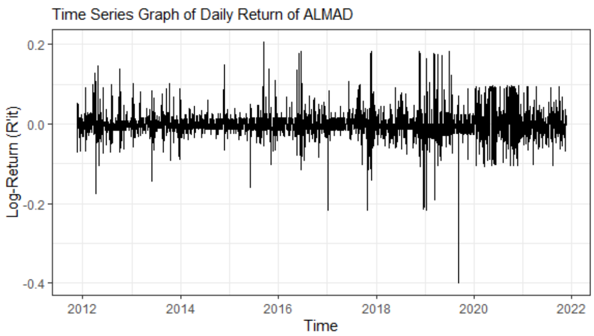

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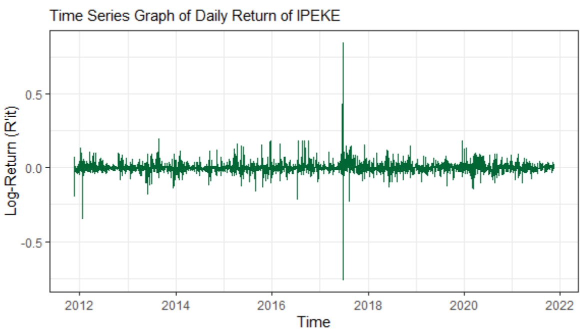
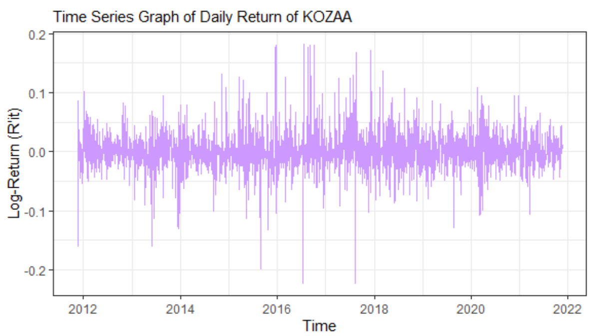
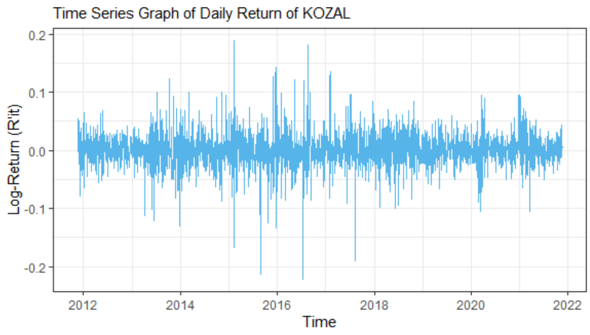
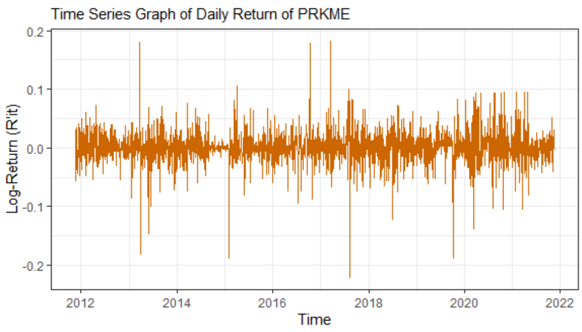




(c) **(d)**





(e) **(f)**

Figure 2. Time Series Plots of Returns on XUTUM and All Mining & Quarrying Companies

Table 3 shows parameter estimates of the GARCH-type models. The constant term of parameter ω, the ψ_1 parameter the effect of shocks/new news on the market on volatility, that is, the short-term conditional variance (ARCH term), the θ_1 parameter represents the effect of the volatility of the previous period on the volatility of the next period, that is, the long-term conditional variance (GARCH term), the ζ_1 parameter indicates the effect of leverage on volatility, the δ parameter shows the power parameter, that is, the dependence of volatility on that period in the conditional variance equations of GARCH-type models. The constant term (ω) of the models is statistically significant at the 95% confidence level, except KOZAL for APARCH model, and the conditions of the models belonging to each company are met. If the model coefficients are to be examined in more detail, the ARCH effect parameter $\psi 1$, which expresses the past shocks, is 0.32576 in ALMAD, while the GARCH effect parameter $\theta 1$, which expresses the effect of the shocks in the previous period from the current period on the volatility of the next period, is 0.55160 in ALMAD. This indicates that approximately 33% of the ALMAD company's return consists of shocks from the past period, and approximately 55% from the shocks of the immediate previous period. Thus, it can be said that the volatility of ALMAD company is heavily affected by the shocks of the previous period. ARCH effect parameter $\psi 1$ is 0.17123 in IPEKE, while the GARCH effect parameter $\theta 1$ is 0.82384 in IPEKE. This indicates that approximately 17% of the IPEKE company's return consists of shocks from the past period, and approximately 82% from the shocks of the immediate previous period. Thus, it can be said that the volatility of IPEKE company is heavily affected by the shocks of the previous period. ARCH effect parameter $\psi 1$ is 0.14491 in KOZAA, while the GARCH effect parameter $\theta 1$ is 0.65552 in KOZAA. This indicates that approximately 14% of the KOZAA company's return consists of shocks from the past period, and approximately 65% from the shocks of the immediate previous period. Thus, it can be said that the volatility of KOZAA company is heavily affected by the shocks of the previous period. ARCH effect parameter $\psi 1$ is 0.05654 in KOZAL, while the GARCH effect parameter $\theta 1$ is 0.92027 in KOZAL. This indicates that approximately 6% of the KOZAL company's return consists of shocks from the past period, and approximately 92% from the shocks of the immediate previous period. Thus, it can be said that the volatility of KOZAL company is heavily affected by the shocks of the previous period. ARCH effect parameter $\psi 1$ is 0.06838 in PRKME, while the GARCH effect parameter $\theta 1$ is 0.92439 in PRKME. This indicates that approximately 7% of the PRKME company's return consists of shocks from the past period, and approximately 92% from the shocks of the immediate previous period. Thus, it can be said that the volatility of PRKME company is heavily affected by the shocks of the previous period. According to these result, it is concluted that volatilitiy of all mining and quarrying companies are heavily affected by the shocks of the previous period. The ζ_1 parameter in the EGARCH model is positive in all companies. This shows that negative shocks affect volatility more than positive shocks. The parameter $\bar{d}$ in the FIGARCH model is positive and significant in all companies. This shows that the variance of returns is predictable. Finally, according to the parameter δ in the APARCH model, it shows that the volatility of KOZAA company is more committed to that period compared to other companies.

Table 3. Model Parameters of Mining & Quarrying Companies

Models	Parameters	Codes of the Mining & Quarrying Companies				
		ALMAD	IPEKE	KOZAA	KOZAL	PRKME
GARCH	ω	0.00026*	0.000087*	0.000232*	0.000023*	0.000001*
	p-value	*0.0000*	*0.0000*	*0.0100*	*0.0036*	*0.0436*
	ψ_1	0.32576*	0.17123*	0.14491*	0.05654*	0.06838*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
	θ_1	0.55160*	0.82384*	0.65552*	0.92027*	0.92439*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
EGARCH	ω	-1.21594*	-0.50248*	-1.66001*	-0.30694*	-1.18074*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0049*	*0.0000*
	ψ_1	0.02147	0.07210*	0.00265	-0.00500	0.02333
	p-value	*0.3056*	*0.0000*	*0.8939*	*0.6557*	*0.1520*
	θ_1	0.80952*	0.91615*	0.75302*	0.95467*	0.83521*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
	ζ_1	0.43900*	0.27375*	0.33595*	0.18603*	0.23555*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
FIGARCH	ω	0.00000*	0.00008*	0.0000*	0.0000*	0.0000*
	p-value	*0.0000*	*0.0000*	*0.0069*	*0.0017*	*0.0095*
	ψ_1	0.42185*	0.14099*	0.28610*	0.68073*	0.04999*
	p-value	*0.0001*	*0.0044*	*0.0000*	*0.0000*	*0.0000*
	θ_1	0.97659*	0.83074*	0.97923*	0.82452*	0.90005*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
	$\bar{d}$	1.00000*	0.95254*	1.00000*	0.37041*	0.40017*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
APARCH	ω	0.00219*	0.00177*	0.0000*	0.00010	0.00931*
	p-value	*0.0412*	*0.0287*	*0.0000*	*0.3659*	*0.0000*
	ψ_1	0.27374*	0.18080*	0.05791*	0.06930*	0.13223*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0002*	*0.0000*
	θ_1	0.63452	0.81317	0.78796	0.91602	0.75105
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
	ζ_1	-0.04361	-0.29670*	-0.00085	0.07181	-0.08255
	p-value	*0.3978*	*0.0000*	*0.9834*	*0.2319*	*0.3177*
	δ	1.32869*	1.15715*	3.09078*	1.59094*	0.77330*
	p-value	*0.0000*	*0.0000*	*0.0000*	*0.0000*	*0.0000*
Note: Parameters marked with '*' indicate parameters that are significant at the 95% confidence level.						

Table 4 shows values of information criteria of models of mining and quarrying companies. This information criterias that the Bayesian information criterion (BIC), the

Akaike's information criterion (AIC), and the Hannan-Quinn information criterion (HQC) as follows:

$$AIC = -2\ln(L) + 2k$$
$$BIC = -2\ln(L) + k\ln(N)$$
$$HQC = -2\ln(L) + 2(\ln(N))k$$

Here, L, N and k are the values of likelihood function evaluated at the parameter estimates, observations (N=2509), and estimated parameters, respectively [34, 35, 36].

According to the values given in Table 4, the best modeling is FIGARCH for ALMAD, EGARCH for IPEKE, FIGARCH for KOZAA, FIGARCH for KOZAL and APARCH for PRKME. So, it was concluded that the GARCH-type model that best models time-varying beta risk differs according to companies.

Table 4. Information Criteria of Models of Mining & Quarrying Companies

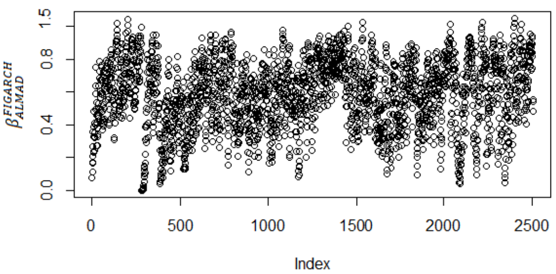
Codes	Models	Information Criteria		
		AIC	BIC	HQC
ALMAD	GARCH	-3.9120	-3.9028	-3.9087
	EGARCH	-3.9147	-3.9031	-3.9105
	FIGARCH	-3.9161*	-3.9045*	-3.9119*
	APARCH	-3.9157	-3.9018	-3.9106
IPEKE	GARCH	-3.6785	3.6692	-3.6751
	EGARCH	-3.7055*	-3.6939*	-3.7013*
	FIGARCH	-3.6820	-3.6704	-3.6778
	APARCH	-3.7018	-3.6879	-3.6968
KOZAA	GARCH	-4.0096	-4.0003	-4.0062
	EGARCH	-4.0027	-3.9910	-3.9984
	FIGARCH	-4.0154*	-4.0038*	-4.0112*
	APARCH	-4.0096	-3.9956	-4.0045
KOZAL	GARCH	-4.2181	-4.2088	-4.2147
	EGARCH	-4.2198	-4.2082	-4.2156
	FIGARCH	-4.2413*	-4.2297*	-4.2371*
	APARCH	-4.2184	-4.2044	-4.2133
PRKME	GARCH	-4.4019	-4.3926	-4.3985
	EGARCH	-4.4870	-4.4753*	-4.4827
	FIGARCH	-3.0921	-3.0805	-3.0879
	APARCH	-4.4892*	-4.4752	-4.4841*
Note: '*' means that the model with the smallest value fits the data better.				

Table 5 shows time-varying beta risks of the model that best models of mining & quarrying companies. When the beta parameter is accepted as a risk measure, it can be said that the model with the highest volatility belongs to the IPEKE company, which varies in the range of [0.0;2.0]. It can be said that investments with beta risk less than 1, ALMAD (0.94485), KOZAL (0.71892), PRKME (0.94485), have lower risk than XUTUM investment while investments with beta risk more than, IPEKE (1.10693) and KOZAA (1.25188), have higher risk than XUTUM investment. The positive beta risks indicate that mining and quarrying companies are in the same direction with the market. The average beta risk of less than 1 indicates that companies are less sensitive to the market while the average beta risk of greater than 1 indicates that companies are highly sensitive to the market. Thus, it is concluded that the sensitivity of the mining and quarrying sector to the market is low, although it can be said that the fact that there are few companies belonging to the sector may affect the results.

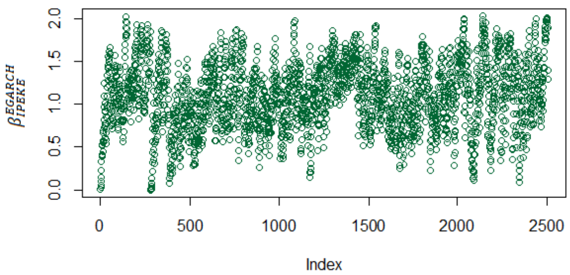
Table 5. Time-varying Beta risk of the Model that Best Models of Mining & Quarrying Companies

		Min.	Max.	Median	Mean	Std. Dev.	Skewness	Kurtosis
ALMAD	$\beta^{FIGARCH}$	0.00000	1.69285	0.97260	0.94485	0.33695	-0.37164	2.58281
IPEKE	β^{EGARCH}	0.00003	2.03011	1.10693	1.10351	0.38936	-0.09527	2.58940
KOZAA	$\beta^{FIGARCH}$	0.00004	2.17894	1.25188	1.21616	0.43370	-0.37164	2.58281
KOZAL	$\beta^{FIGARCH}$	0.00003	1.28806	0.74004	0.71892	0.25638	-0.37164	2.58281
PRKME	β^{APARCH}	0.00004	1.69285	0.97260	0.94485	0.33695	-0.37164	2.58281

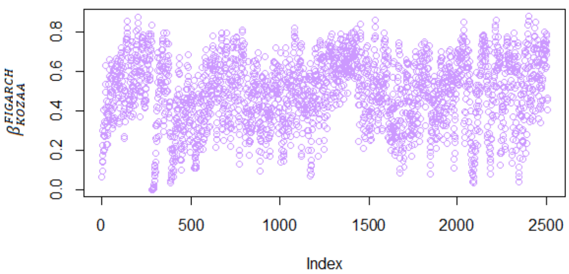
Figure 3 shows the time series graphs of beta risks on the quarrying and mining companies and Figure 4 shows mean, standard deviation, skewness and kurtosis of beta risk and daily return, respectively.



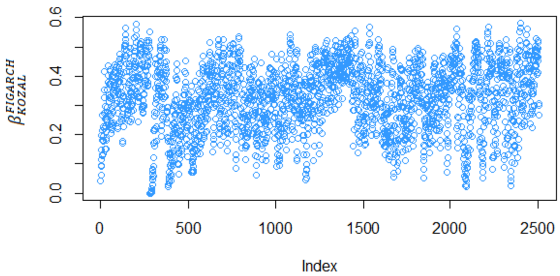
(a)



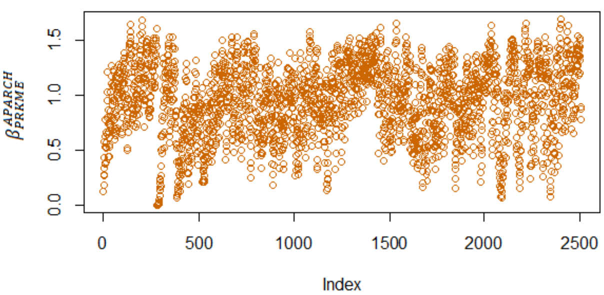
(b)



(c)

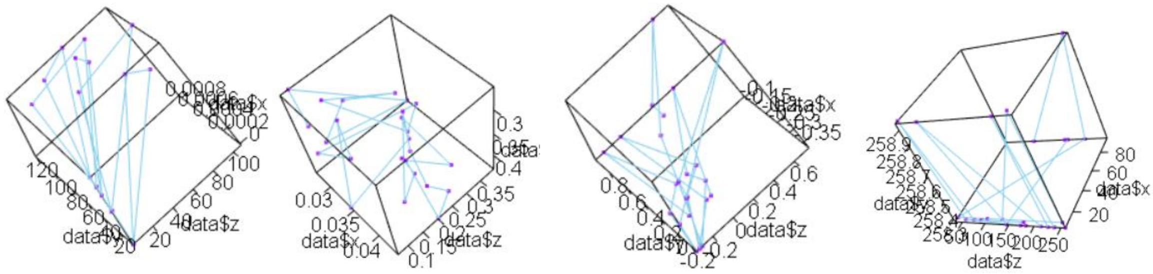


(d)



(e)

Figure 3. Time-varying Beta risk of the Model that Best Models of Mining & Quarrying Companies



(a) **(b)** **(c)** **(d)**

Figure 4. Mean, Standard Deviation, Skewness and Kurtosis of Beta Risk and Daily return

5. CONCLUSION AND DISCUSSION

The research data of this paper covers the dates of November 18, 2011 to November 18, 2021. In this date range, a portfolio was created by taking daily frequency data of all quarrying and mining companies in the BIST National All index. This paper was conducted for the beta risk or systematic risk, which is the risk that the investors who create the risk cannot avoid, for the first time BIST National All index and all companies belonging to mining and quarrying are used the daily frequency data on the date of last ten years which 18 November 2011 to 18 November 2021. For the time-varying beta risk parameters, the Conditional Capital Asset Pricing Model (C-CAPM) is used. Time-varying Linear Market Model (Tv-LMM) that is a data production model consistent with C-CAPM is modeled with GARCH, EGARCH, FIGARCH and APARCH that are univariate GARCH type models. In this paper, three main conclusions were reached and contributed to the practice literature. Firstly, according to the model benchmarking criterias for GARCH type model which best models the time-varying beta risk; It was found that FIGARCH for ALMAD, EGARCH for IPEKE, FIGARCH for KOZAA, FIGARCH for KOZAL and APARCH for PRKME. So, it has been found that GARCH-type models are not superior to each other. Secondly, the date 2020 was defined as the COVID-19 global epidemic by the WHO was March 11, 2020, the date of the 59th presidential election in the USA was December 12, 2020, the economic crisis observed in the Turkish economy in 2018, and the effects on the markets consequently of the global economic crisis experienced in 2008-2012 effect, that is extreme fluctuations, was clearly observed and there is a leverage effect in all companies on this period. Finally, when beta risk and standard deviation are considered as risk measures, it has been found that IPEKE is the riskiest company in all mining and quarrying companies in the BIST National All Index. In addition, it has been determined that mining and quarrying companies are in the same direction with the market and there is a leverage effect in all companies on this period. In future studies, it is recommended to compare the performance of models in different financial markets, periods and frequencies and to create investment portfolios.

CONFLICT OF INTEREST

The author stated that there are no conflicts of interest regarding the publication of this article.

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