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Financial Decisions and Value-at-Risk: Empirical Evidence from BIST 100 Companies

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Abstract

This study examines the relationship between financial decisions and the value-at-risk (*VaR*) of companies operating in the Turkish stock market. The study contains semi-annual data of non-financial BIST 100 Index companies spanning from January 2010 to June 2023. Companies' *VaR* are calculated using Monte-Carlo simulation, bootstrap, delta-normal, and historical simulation methods and included in separate econometric models as dependent variables. Financial decisions are represented through financial ratios in line with the basic principles of corporate finance and included as explanatory variables in econometric models. The study employs a five-stage panel data methodology.

Findings reveal that the impact of financial decisions regarding working capital management, capital structure, dividend pay-out, and growth policies on companies' *VaR* differ according to the *VaR* calculation method. Notably, findings show that financial decisions explain the changes in *VaR* calculated by Bootstrap method with the highest success rate, aligning with existing finance literature. Prudent financing policies and flexible investment strategies in working capital management, enhanced profitability and financial performance, and sales growth exhibit dampening effects on *VaR*. Conversely, heightened leverage and long-term borrowings, decisions to pay-out dividends, and growth in foreign investments have increasing effects on *VaR*. Furthermore, the study identifies the Covid-19 pandemic as exerting a negative influence on VaR.

Keywords: Value-at-Risk, Financial Management, Risk Management, Panel Data Analysis.

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1. INTRODUCTION

Risk can be defined as the likelihood that fluctuations in the returns on financial assets will diverge from expectations. Losses due to uncertainty stemming from time, changing market conditions and unpredicted or unexpected events underscore the necessity for companies to implement effective risk management systems (Korkmaz and Kuzay, 2022). Companies inherently carry a level of risk due to various factors such as market dynamics, competition, regulatory changes, and economic fluctuations. The degree of risk associated with a company depends on factors such as its industry, financial health, management decisions, and exposure to external shocks. Understanding and managing risk is a critical aspect of corporate governance and strategic decision-making. Companies employ various risk management techniques and strategies to mitigate and manage the risks they face, aiming to protect their assets, optimize returns, and ensure long-term sustainability. Effective risk management involves identifying, assessing, prioritizing, and responding to risks in a proactive manner. It often entails implementing policies, procedures, controls, and risk mitigation measures tailored to the specific needs and circumstances of the company. Businesses seeking protection against risks employ a variety of risk management models, including asset pricing models, option pricing models, stress tests, value-at-risk methods, and RiskMetrics (Jorion, 2000).

Historically, one of the most significant events that catalyzed a paradigm shift in the understanding of risk management was the establishment of the Bretton Woods system. The Bretton Woods system, based on a fixed exchange rate regime, was established in 1944 in order to rebuild the international financial system, which was significantly damaged as a result of the Great Depression of 1929 in the United States and the subsequent World War II, and to ensure economic stability in the post-war world. While the Bretton Woods system proved successful to a certain extent until the 1970s, its dissolution in 1973 ushered in a new era marked by increased risks across the financial landscape, including interest rate risk, exchange rate risk, and market risk (Topaloğlu and Kurt Cihangir, 2022). The inherently risk-prone nature of financial markets has increased the need for scientific analysis of financial risks by various segments such as portfolio investors, financial managers, stakeholders, and fund managers. In 1952, the mean-variance model developed by Harry Markowitz significantly changed the approach to risk management in portfolio investments. Subsequently, in 1956, Russell Gallagher emphasized the significance of risk management and risk managers in organizational activities. Although the emergence of risk management as a discipline that dates back to the 1950s, its evolution accelerated during the 1980-2000 period due to the implementation of neo-liberal economic policies by many countries and the ensuing major financial crises. Consequently, risk management, particularly in sectors like banking, transitioned from being merely a corporate requirement to a legal obligation (Ural et al., 2022).

It is only possible for investors and financial managers to develop hedging policies by measuring and modeling risk. Significant fluctuations in financial markets and financial crises in many countries, particularly after 1970, revealed the inadequacy of traditional risk measurement methods. The value-at-risk (*VaR*) method, developed by JP Morgan in 1994 and introduced as part of the RiskMetricks analysis program, quickly became one of the fundamental measuring methods in risk management. *VaR*, which is used to measure market risk, is a useful risk management tool that is based on the calculation of the maximum potential loss rate that a financial instrument, investment or portfolio may encounter at a certain confidence level in a certain time frame, is easily measurable and provides a single numerical representation of risk. Essentially, *VaR* is a measure of losses resulting from normal market movements (Linsmeier and Pearson, 2000), and is calculated using historical price data. However, firm-specific factors such as investment decisions, financing strategies, and dividend pay-out policies play a crucial role in shaping a companies' risk profile and its sensitivity to external factors. Incorporating these firm-specific considerations is essential for comprehensive and effective risk management practices. *VaR* is used by different segments such as portfolio managers, financial managers, financial and non-financial institutions, regulators and brokers for purposes such as reporting, resource allocation, and performance evaluation (Korkmaz and Kuzay, 2022). Several methods are employed to calculate companies' *VaR*. *VaR* calculation methods are usually classified by whether they are parametric or non-parametric. Non-parametric methods such as Monte-Carlo simulation and historical simulation, and parametric methods such as delta-normal or variance-covariance method and GARCH method are commonly utilized for calculating *VaR*. Additionally, the bootstrap method serves as a versatile method that can be applied in both parametric and non-parametric contexts for *VaR* calculation (Butler, 1999; Li, 2019). Each *VaR* calculation method has its own assumptions, advantages, and limitations, and the choice of method depends on factors such as the characteristics of the financial assets, the availability of data, and the preferences of risk managers or investors.

VaR, as a critical risk management tool, is a pivotal indicator reflecting the market risk inherent in firms or portfolios. Portfolio managers, stakeholders, and financial managers, in their roles, are obligated to formulate and execute financial strategies aimed at mitigating the market risk of the firms they oversee, while remaining attentive to market developments. Consequently, understanding the impact of financial decisions on a companies' *VaR* is paramount, not only for financial managers in crafting prudent financial policies but also for investors and stakeholders in making informed decisions. By employing robust econometric methodologies, this study aims to elucidate the intricate relationships between financial decisions and companies' *VaR*, and to answer three important questions: (1) Are financial decisions pivotal in risk management? (2) Do *VaR* methods vary concerning corporate finance principles? (3) Which VaR method best suits non-financial companies operating in Turkey in accordance with corporate finance principles? The study specifically seeks to understand how investment decisions, financing strategies, and dividend pay-out policies influence potential losses of companies in the concept of different *VaR* models. Furthermore, the study seeks to ascertain the optimal *VaR* method in risk management for companies operating in Turkey by evaluating the impact of financial decisions on *VaR* using robust econometric methodologies. The study defines the most effective *VaR* method in risk management as the most suitable approach aligned with corporate finance principles. Through empirical analyses, this study aspires to contribute to the existing body of knowledge on corporate finance and financial risk management. To the best of our knowledge, this paper is the first attempt to investigate the impact of financial decisions on *VaR* and compare *VaR* methods in the context of corporate finance. Revealing the impacts of financial decisions on *VaR* calculated by different methodologies through empirical analyses presents the unique value of the study. Additionally, the limited scope of existing literature on the relationship between *VaR* and corporate finance implementations underscores the potential significance of this study in contributing to academic literature.

It is believed that the study will help better understand the role of investment, financing, and dividend pay-out policies in risk management, financial managers in shaping the risk management strategies and the choice of *VaR* methodology, and investors and stakeholders to direct their investments according to their perception of risk. The study contains semi-annual market and financial statement data of non-financial BIST 100 Index companies operating in Turkey spanning from January 2010 to June 2023. Although the widest range of data on manufacturing BIST 100 companies is preferred, this study has limitations in both time and cross-sectional dimensions. Additionally, the study's focus solely on publicly traded non-financial companies presents another constraint. Furthermore, the study's modeling framework excludes variables beyond financial decisions. In terms of the modeled variables, the study provides important findings in the context of corporate finance but does not provide findings on the relationship between *VaR* and market performance and macroeconomic variables. The study consists of six main sections. Following the introductory section where the theoretical framework is presented, Section 2 presents the relevant literature. Section 3 provides detailed information on the purpose, scope, data set, and variables. Section 4 explains the methodology and the econometric design. Section 5 presents the findings of the panel regression analysis, evaluations, and discussion. Section 6, the final section, includes conclusions and policy recommendations.

2. LITERATURE REVIEW

Studies in the literature commonly assess *VaR* across specific investment instruments, evaluate *VaR*'s efficacy in financial risk management, or compare *VaR* methods in a methodological context. The primary objectives of this study are to evaluate *VaR* methods based on theoretical finance, identify the most suitable *VaR* method for firms operating in Turkey within a theoretical framework, and offer insights to financial managers and investors. Firm-level *VaR* is calculated using four distinct *VaR* methods over 6-month periods, utilizing daily closing price data of firms' stocks. Consequently, the literature review section encompasses studies examining *VaR* methods as tools for financial risk management, comparing *VaR* methodologies, and suggesting optimal *VaR* methods for risk management within specific markets or investment instrument groups.

Hendrics (1996) investigated the effectiveness of *VaR* methods and their superiority over each other and found that no *VaR* method is significantly superior to the others. In a similar study, Linsmeier and Pearson (1996) stated that the choices between *VaR* methods will differ according to the areas that the risk manager considers most important. Using data on securities traded in the USA, UK, France and Japan stock markets, Jackson et al. (1998), reported that simulation methods yield better results than parametric methods in return series where the normal distribution is not valid. Analyzing *VaR* in Dutch government bonds portfolios, Vlaar (2000), stated that the success of Monte-Carlo and historical simulation methods depends on the sample size and time dimension, and the success of delta-normal method depends on whether the data conform to the normal distribution.

Examining investors' use of *VaR* for market risk management in optimal dynamic portfolios and wealth/consumption policies Basak and Shapiro (2001) find that *VaR* risk managers often optimally choose to be more exposed to risky assets than non-risk managers and consequently suffer larger losses. Campbell et al. (2001) developed a portfolio selection model using a mean-variance model approach with maximum return and minimum *VaR* constrained optimization model and concluded that the non-normal character of expected returns and the investment horizons affect *VaR* and optimal portfolio selection. Examining the effectiveness of *VaR* methods used by USA commercial banks, Berkowitz and O'Brien (2002) found that *VaR* values calculated using the GARCH model for volatility measurement are quite close to market risk and can be checked by backtesting. Glasserman et al. (2002) developed two methods for efficient calculation of *VaR* when risk factors have heavy-tailed distributions and note that numerical results on various test portfolios generally indicate large variance reductions, that the Monte-Carlo method based on quadratic convergence can operate with lower variance than the ordinary Monte-Carlo method, and that both methods overcome the difficulties associated with *VAR* computation involving heavy-tailed risk factors.

Examining the the parametric *VaR* method in the Turkish capital markets, Akan et al. (2003) state that the foreign exchange policies implemented in Turkey have significant effects on the parametric method. Cabedo and Moya (2003), while analyzing the historical simulation method with three different approaches, developed a new method that takes into account the estimation errors in the distributions with the autoregressive moving average method instead of directly using the past returns and stated that the method they developed is quite compatible with the movements in oil prices and provides an effective risk measurement. Giot and Laurent (2003) model *VaR* for daily asset returns using a collection of parametric univariate and multivariate models of the ARCH class based on the skewed student distribution and propose the use of an APARCH model based on the skewed student distribution to fully account for the thick left and right tails of the return distribution. In another study, Giot and Lauren (2004), compare the performance of an ARCH-type model using daily returns and a model based on daily realized volatility using intraday returns for *VaR* calculation 1 day ahead and find that both models are equivalent in terms of performance.

Bozkuş (2005), who found that *VaR* methods show a positive deviation in data with heavy-tailed distributions, stated that as an alternative method, expected loss methods are more consistent since they do not carry tail risk. In a similar study, Harmantzis et al. (2006) also found that expected loss models are more successful in risk estimation than *VaR* methods since the distributions without heavy-tail risk. Comparing the *VaR* results calculated for short and long investment positions by 7 different GARCH models and the RiskMetrics method for 12 stock market indices and 4 foreign exchange rates, So and Yu (2006) found that both stationary and fractionally integrated GARCH models are more successful than the RiskMetrics method in calculating 1% *VaR*. Comparing *VaR* calculation methods using more than 30 years of daily return data on NASDAQ Composite Index, Kuester et al. (2006) found that the *VaR* model calculated by a hybrid method combining a heavy-tailed GARCH filter with an approach based on extreme value theory performed best. Lin et al. (2006) investigated the usability of student t distribution based *VaR* methods in market risk measurement, has observed that the estimation with bootstrap method for the quantile and tail probability with importance resampling is more efficient than the naive Monte-Carlo method. Lin et al. (2006) also reported that the use of the student t distribution gives more accurate results than the normal distribution for *VaR* calculations above 98.5%. Chipalkatti et al. (2006) examined the relationship between *VaR* and abnormal returns and found that potential losses do not have any significant relationship with *VaR*.

Usins the *VaR* method to analyze the risk of exchange rate and stock market indices in the Turkish stock market Gürsakal (2007), found that the stock market index has a higher risk than the exchange rate. Comparing Monte-Carlo, historical and delta-normal methods, Özden (2007) states that all three methods yield similar *VaR* values, yet the lowest *VaR* value is obtained by delta-normal method. Aktaş (2008) analyzed the risks of the parametric *VaR* method in Turkish capital markets and found that the variance-covariance method is risky for Turkish capital markets due to the high variability in the values of financial instruments and the non-normal distribution of the data. In another study conducted in the Turkish capital markets, Taş and İltüzer (2008) performed *VaR* calculations for BIST30 Index and Government Domestic Debt Securities portfolios by using normal distribution and student t distribution-based Monte-Carlo simulation methods and found that the student t distribution-based approach yields values closer to the actual values. Analyzing the effect of liquidity risk on *VaR* calculations, Zheng et al. (2008) stated that liquidity reduces the potential loss in *VaR* calculations and suggested the use of Monte-Carlo simulation method in *VaR* calculations to avoid such losses.

On a hypothetical portfolio consisting of Euro, gold and US Dollar in Turkish capital markets, Demireli and Taner (2009) stated that the most appropriate *VaR* method for Turkish capital markets is the Monte-Carlo simulation method. Kayahan and Topal (2009) analyzed the daily *VaRs* of firms' currency portfolios and stated that the historical simulation method is an effective method for *VaR* calculations. Analyzing the Turkish capital markets’ *VaR*, Korkmaz and Bostancı (2011) reported that *VaR* calculations based on GARCH models are successful in volatility calculations.

Brandolini and Colucci (2012), who compare *VaR* methods with backtesting in international capital markets, find that the Monte-Carlo filtered bootstrap method yields more consistent results than historical simulation for all stock indices tested. In a similar study, Mentel (2013) compares *VaR* methods in the Polish capital market and finds that the Monte-Carlo simulation method yields more consistent results than the historical simulation method. Starting from the hypothesis that banks using advanced *VaR* models should have lower *VaR*, Bostancı and Korkmaz (2014) use historical volatility, historical simulation, EWMA, GARCH(1,1), GARCH(1,1)-bootstrap and GARCH(1,1)-GED methods, they could not confirm the hypothesis that advanced *VaR* methods such as GARCH(1,1)-bootstrap and GARCH(1,1)-GED would provide lower *VaR*. Contrary to Avşarlıgil et al. (2015), who found that the variance-covariance method is the most successful method when the *VaR* values calculated for sports firms are backtested, Oppong et al. (2016) found that the Monte-Carlo simulation method is the most successful method in their study on Ghana stock markets, as in Brandolini and Colucci (2012) and Mentel (2013).

Bams et al. (2017) compare implied volatility and historical volatility based *VaR* estimations on S&P500, Dow Jones and Nasdaq indices and find that GJR-GARCH based *VaR* estimations outperform implied volatility based *VaR* estimations. Laporta et al. (2018) test different *VaR* forecasts for energy commodities and find that Conditional Autoregressive Value-at-Risk (CAViaR) and Dynamic Quantile Regression (DQR) models are more successful than other models. Kavrar and Yılmaz (2019), on the other hand, emphasized the importance of *VaR* method in risk management in their study on a hypothetical portfolio consisting of financial instruments such as stocks, foreign exchange rates and gold, and stated that the historical simulation method has shortcomings. Liu et al. (2020), who performed *VaR* prediction with the RiskMetrics method in cryptocurrencies, stated that the RiskMetrics method can provide valuable bases for risk modeling in cryptocurrencies under primary backtesting conditions. Işıldak (2021), who examines the diversification effect of including gold, foreign exchange and stock indices in the same portfolio with *VaR* methods for different confidence levels, finds that the *VaR* values of financial instruments increase as the confidence level decreases and the *VaR* value of the portfolio is lower than the *VaR* value of each financial instrument.

In a more recent study, Topaloğlu and Kurt Cihangir (2022) examined the relationship between *VaR* and stock returns in the Turkish banking market and detected a bidirectional causality relationship between stock returns and Monte-Carlo *VaR*, while no causality relationship is detected between delta-normal and bootstrap *VaRs* and stock returns. Likitratcharoen (2023), who used *VaR* methods to estimate extreme market stress in the cryptocurrency market during the periods Covid-19 pandemic and the Russia-Ukraine war, stated that the historical simulation method is the most appropriate method for *VaR* calculations in cryptocurrencies. In a similar study, Trucíos and Taylor (2023) stated that the generalized autoregressive score (GAS) model is an appropriate model for *VaR* and expected loss estimation in the cryptocurrency market. In another recent study, Türkyılmaz (2023) conducted *VaR* estimation with long-memory asymmetric volatility models during Covid-19 pandemic in gold market and found that *VaR* estimates based on volatility models that consider long-memory and asymmetric effects are appropriate in gold market.

Many scientific studies have been conducted on the *VaR* methods, which is one of the most popular methods in risk management. A review of the literature reveals that there is no consensus on the most appropriate approach to be used in *VaR* calculations, but there is a consensus that *VaR* methods are very useful in risk management. This study uses several VaR calculation methods to represent companies' market risk, and unlike the literature compares them in the context of theoretical corporate finance and reveals the role of financial decisions in risk management.

3. DATA AND VARIABLES

This study investigates the relationship between financial decisions and value-at-risk in BIST 100 Index companies. The dataset comprises stock market data and financial statement data from 25 non-financial firms consistently listed in the BIST 100 Index between January 2010-June 2023, with regularly accessible data. Financial sector firms and holdings are excluded from the study due to differences in their financial statements. The study period was selected based on the most recent dates conducive to obtaining consistent findings and reliable data that could be extrapolated to larger populations. As such, data from crisis periods, which might introduce inconsistencies in econometric analyses, were omitted from the scope when determining the study period. This approach aimed to ensure the robustness and generalizability of the study's findings while minimizing the potential distortions associated with crisis-related data. Commencing from 2010 serves to mitigate the potential influence of the 2008 mortgage crisis, thereby ensuring more reliable and unbiased econometric analyses. By 2010, the effects of the crisis had largely subsided in Turkey. Furthermore, the study's end period is determined by the most recent available annual financial statement data of the firms within the sample. It's important to note that the study faces limitations in both time and cross-sectional dimensions. Focusing solely on publicly traded non-financial companies and excluding market performance and macroeconomic indicators present another limitation of the study. The dataset spans 27 periods from June 2010 to June 2023, with *VaRs* calculated using semi-annual stock market data and financial indicators derived from semi-annual financial statements. Consequently, the study dataset constitutes panel data, encompassing a horizontal cross-sectional dimension of 25 companies and a time dimension spanning 27 periods from June 2010 to June 2023. Stock market codes and titles of the BIST 100 Index companies included in the study are detailed in Table 1.

The study period spans the duration following October 2021, characterized by significant depreciation of the Turkish Lira. This depreciation may result in heightened TL-denominated liabilities and borrowing costs for companies holding foreign currency debt, while also artificially inflating investments for firms with foreign currency receivables. Furthermore, the devaluation of the local currency, influenced by its impact on inflation, could escalate input expenses and diminish profit margins. The high volatility in exchange rates and the devaluation of the local currency may necessitate the revaluation of firms' assets and liabilities, posing challenges in accurately reflecting financial statements. These factors warrant consideration when evaluating the study's findings.

Table 1. Companies Included in the Study

No	Code	Firm Title	No	Code	Firm Title
1	AEFES	Anadolu Efes Biracılık ve Malt Sanayi A.Ş.	14	KOZAL	Koza Altın İşletmeleri A.Ş.
2	AKSA	Aksa Akrilik Kimya Sanayii A.Ş.	15	MGROS	Migros Ticaret A.Ş.
3	ARCLK	Arçelik A.Ş.	16	PETKM	Petkim Petrokimya A.Ş.
4	ASELS	Aselsan Elektronik Sanayi ve Ticaret A.Ş.	17	SISE	Türkiye Şişe ve Cam Fabrikaları A.Ş.
5	BIMAS	BİM Birleşim Mağazaları A.Ş.	18	TAVHL	Tav Havalimanları A.Ş.
6	DOAS	Doğuş Otomotiv Servis ve Ticaret A.Ş.	19	TCELL	Turkcell İletişim Hizmetleri A.Ş.
7	ECILC	Eczacıbaşı İlaç, Sınai ve Finansal Yatırımlar	20	OTKAR	Otokar Otomotiv ve Savunma Sanayi A.Ş.
8	ENKAI	Enka İnşaat ve Sanayi A.Ş.	21	TOASO	Tofaş Türk Otomobil Fabrikası A.Ş.
9	EREGL	Ereğli Demir ve Çelik Fabrikaları T.A.Ş.	22	TTKOM	Türk Telekomünikasyon A.Ş.
10	FROTO	Ford Otomotiv Sanayi A.Ş.	23	ULKER	Ülker Bisküvi Sanayi A.Ş.
11	GUBRF	Gübre Fabrikaları T.A.Ş.	24	KRDMD	Kardemir Karabük Demir Çelik San. ve Tic. A.Ş.
12	KOZAA	Koza Anadolu Metal Madencilik İşletmeleri A.Ş.	25	TUPRS	Tüpraş, Türkiye Petrol Rafinerileri A.Ş.
13	THYAO	Türk Hava Yolları Anonim Ortaklığı			

Four different *VaR* methods are employed to represent the companies' *VaR* in a given period. *VaR* calculated by Monte-Carlo simulation, bootstrap, delta-normal and historical simulation methods are included as dependent variables in econometric models. *VaR* calculated by different methods may show significant differences. *VaR* calculations are conducted for 6-month periods using the closing data of firms' stocks. Specifically, it is assumed that firms' risks remain constant over risk horizon (6-month periods). Nonetheless, over the study's duration spanning 27 6-month periods, changes in firm risk are allowed, and the data are transformed into panel data to facilitate analysis. This methodological approach enables the examination of whether fluctuations in *VaR* at the firm level can be elucidated by various firm specific factors such as investment, financing, and dividend pay-out decisions. Financial decisions are analyzed through financial ratios of companies in line with the basic principles of corporate finance. Three basic components of financial management: investment and growth policy, financing policy and dividend pay-out policy are represented through various financial ratios, along with financial performance indicators. Within this framework, companies' investment and growth policy is represented using working capital investmens, growth in assets, growth in investments and growth in sales, companies' financing policy is represented using current ratio as short-term financing policy indicator and leverage ratio and long-term debts ratio as long-term financing policy indicator. Financial performance, on the other hand, is represented by return on assets and Tobin's Q. Fixed asset investment ratio representing the investment policy and short-term debts ratio representing the financing policy are excluded from the econometric models as they are detected to cause multi-collinearity problems. Financial decisions and performance variables are included as explanatory variables in econometric models. To enhance the significance of the econometric models and mitigate inconsistencies and deviations in estimations, the standard deviations of firms' stock returns for the relevant period are incorporated into the models as control variables. Finally, a dummy variable is included in the model to examine the impact of the Covid-19 pandemic on companies' *VaR*. The explanatory variables are presented in Table 2.

Table 2. Explanatory Variables

Variable Group	Variables	Acronym	Calculation
Investment and Growth policy	Working capital ratio	WCR	Current assets/Total assets
	Growth in assets	GIA	Percentage change in total assets between periods t and t-1
	Growth in sales	GIS	Percentage change in net sales between periods t and t-1
	Growth in investments	GII	Percentage change in investments between periods t and t-1
Financing policy	Current ratio	CR	Current assets/Short-term borrowings
	Leverage ratio	LR	Total debts/Total assets
	Long-term debts	LTD	Long-term debts/Total assets
Dividend pay-out policy	Dividend pay out	DPP	Dummy variable with value 1 if dividend is payed out, and value 0 if not
Financial performance	Return on assets	ROA	Net profit/Total assets
	TobinQ	TOBINQ	(Total assets+Market value of equities-Book value of equities)/Total assets
Dummy variable	Covid-19 pandemic	COVID	Dummy variable with value 1 for the period 2020:06-2021:12 and value 0 for other periods
Control variable	Standart deviation	SD	Standard deviation of stock return

Percentage transformation is applied to the variables, in order to reveal the change in *VaR*, caused by a 1-unit change in an independent variable. In addition to the period and sample limitations, there is an important limitation in the study such as the fact that the effects of macroeconomic factors and market performance of firms on the *VaR* are not included in the models. The variables that constitute the data set of the study are obtained from the Financial Information News Network (FINNET) database.

4. METHODOLOGICAL DESIGN AND ECONOMETRIC MODELS

As presented in the literature review, there are many methods used in *VaR* calculation. This study employes Monte-Carlo simulation, bootstrap, delta-normal and historical simulation methods in *VaR* calculation. Monte-Carlo simulation method is recognized as a powerful and flexible calculation method (Boyle et al., 1997). Monte-Carlo simulation method is a modeling process created by determining the statistical distributions of the parameters in a computer environment with stochastic simulation techniques. (Fıkırkoca, 2003). The historical simulation method, on the other hand, involves the calculation of the possible gain and loss distribution of the portfolio by simulating the changes in risk factors according to the scenarios by generating various scenarios over the historical data of the financial instruments included in the portfolio for a certain period (Türker, 2009; Gökgöz, 2006). The historical simulation method, which is non-parametric and based on real market data, can be used in portfolios consisting of non-linear and non-normally distributed financial instruments (Jorion, 1997). The most widely used method in *VaR* calculations is the variance-covariance method, also known as the delta-normal or RiskMertics method, developed by JP Morgan in 1994. In the variance-covariance method, the standard deviation values of the investment instruments are calculated using historical time series and volatility matrices are formed by multiplying by the value obtained from the normal distribution table for a certain confidence level. The variance-covariance matrix is obtained by multiplying the volatility matrix by the correlation table (Korkmaz and Pekkaya, 2021). The *VaR*, which is obtained by multiplying the variance-covariance matrix by the weights of financial instruments in the portfolio, expresses the maximum possible loss that a portfolio investor may face at a certain confidence level in a given period. Another *VaR* method applied to financial risk management in recent years in the finance literature is the bootstrap method (Efron, 1979; Efron and Tibshirani, 1993; Jorion, 2000; Lin et al., 2006). The bootstrap algorithm basically approximates the *VaR* distribution of the investment using the bootstrap analog and then uses the analog to approximate the *VaR* of the investment. As a statistical resampling method, both parametric and non-parametric approaches can be developed for the bootstrap algorithm. The parametric bootstrap process consists of two stages. In the first stage, observed data are used to estimate the unknown parameters of the given distribution, while in the second stage, the sampling distribution of *VaR* is generated using the bootstrap algorithm from the estimated distribution. In the non-parametric bootstrap process, observed data are used to construct the sampling distribution of *VaR* without any assumption on the underlying distribution (Lin et al., 2006).

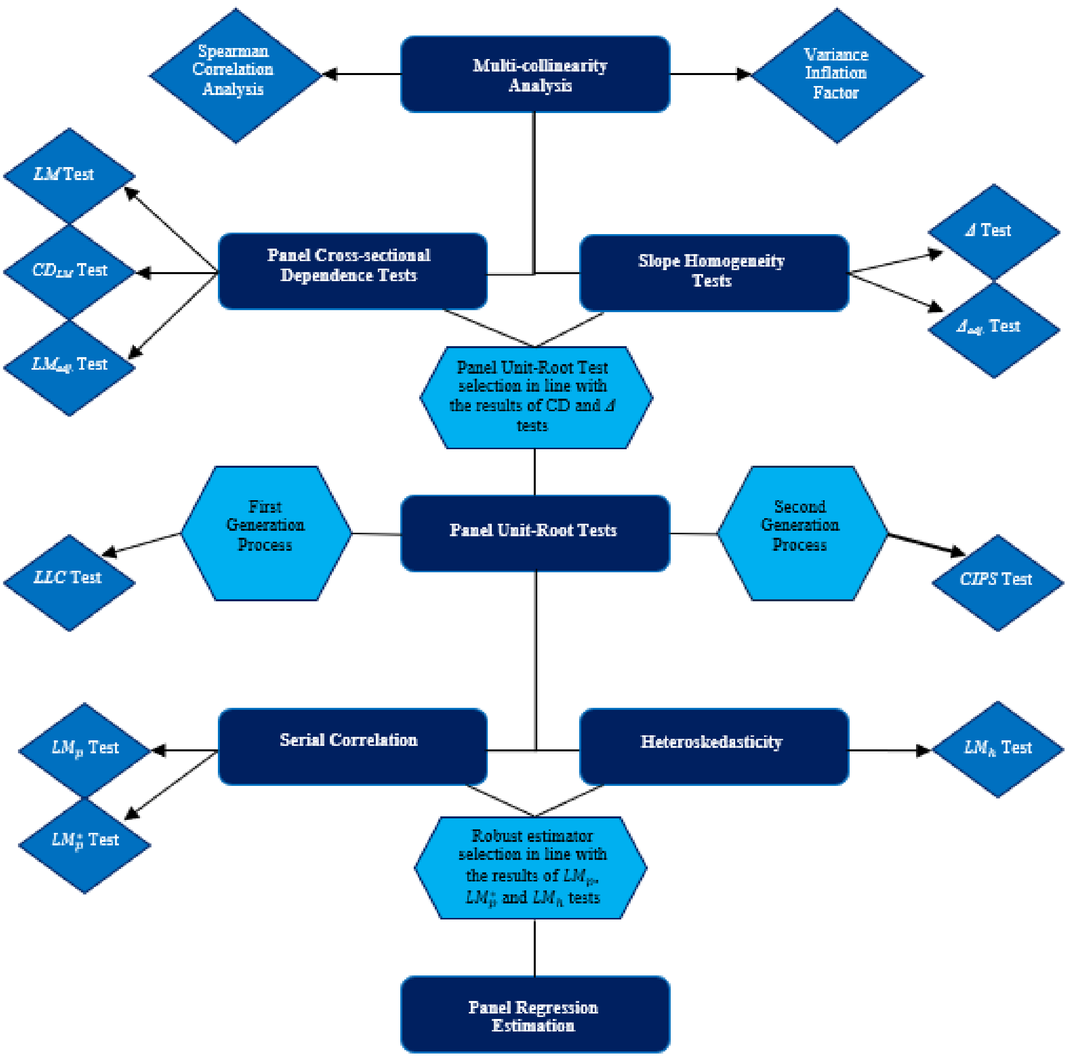
The study follows a five-stage panel regression methodology. In the first stage, the muti-collinearity in the models are analyzed by using Spearman correlation analysis and Variance Inflation Factor (VIF) analysis. In the second stage, the cross-secitonal dependency in variables are tested using Breusch and Pagan (1980) LM, Pesaran (2004) CD_{LM} and Pesaran, Ullah and Yamagata (2008) LM_{adj} tests, while the homogeneity/heterogeneity properties of the series are examined using Pesaran and Yamagata (2008) delta ($\tilde{\Delta}$) and delta adjusted ($\tilde{\Delta}_{adj}$) tests. In the third stage, the stationarity of the series is tested using the Levin, Lin and Chu (2002) *LLC* test, a first generation unit root test, and the Pesaran (2007) *CIPS* test, a second generation unit root test, in line with the results of the cross-section dependence test and slope homogeneity tests. In the fourth stage, the panel regression models are tested for serial-correlation using the Baltagi and Li (1991) LM_p and Born and Breitung (2016) LM_p^* tests, and tested for heteroskedasticity using Breusch and Pagan (1979) LM_h test. The Cross-section SUR (PCSE) robust estimator based on the Period Corrected Standard Error (PCSE) methodology developed by Beck and Katz (1995) is used to estimate the models with time or cross-sectional heteroskedasticity and serial-correlation problems. In the fifth and final stage, the developed models are estimated by panel regression analysis and the results are obtained. Assumption tests and analyses were conducted using Eviews 12 and Gauss 22, two of the most frequently used econometric analysis software packages. Figure 1 shows the flowchart of the methodological approach adopted in the study.

A total of four panel regression models were developed to examine the relationship between *VaR* and financial decisions in BIST 100 companies. Each panel regression model includes a different *VaR* variable as the dependent variable. The explanatory variables in the models remain consistent and are outlined in Table 2. Henceforth, the models examining the relationships between *VaR* values calculated by Monte-Carlo simulation, historical simulation, delta-normal, and bootstrap methods, and financial decisions will be denoted as Model MonteCarlo, Model Bootstrap, Model Delta, and Model Historical, respectively. The representative panel regression model and the null hypothesis provided in equation (1) remain consistent across all models.

$$VaR_{it} = \beta_0 + \beta_1 CR_{it} + \beta_2 WCR_{it} + \beta_3 LR_{it} + \beta_4 LTD_{it} + \beta_5 DPP_{it} + \beta_6 ROA_{it} + \beta_7 TOBINQ_{it} + \beta_8 GIA_{it} + \beta_9 GIS_{it} + \beta_{10} GII_{it} + \beta_{11} COVID_{it} + \beta_{12} SD_{it} + u_{it} \quad (1)$$

H_0: Financial decisions have no effect on *VaR*.

Figure 1. Methodological Design



5. FINDINGS AND DISCUSSION

This section first analyzes the characteristics of the variables included in the models through descriptive statistics. Then, the test results obtained from multi-collinearity, horizontal cross-section dependence, slope homogeneity, stationarity, serial correlation and heteroskedasticity tests are presented. Following the estimator specification tests, the results of panel regression analysis are reported and interpreted.

5.1. Descriptive Statistics

Descriptive statistics and Jarque-Bera normality test results for the series in the balanced panel data set are presented in Table 3. Descriptive statistics show that VaR_{Delta} has the highest and $VaR_{MonteCarlo}$ has the lowest mean and standard deviation among *VaR* variables. The independent variables with the highest and lowest mean and standard deviation values are *GIA* and *LR*, respectively. *SD*, the control variable, has a higher mean (2.312) than all independent variables. All variables, except for *DPP*, are right-skewed, and all variables are leptokurtic. The findings of the normality test reveal that all variables has statistically significant Jarque-Bera test statistics, indicating that the variables are not normally distributed.

Table 3. Descriptive Statistics and Normality Test

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jaque-Bera
$VaR_{MonteCarlo}$	0.061	0.015	1.601	-0.517	0.318	1.059	4.792	216.4***
$VaR_{Bootstrap}$	0.122	-0.001	3.324	-0.671	0.522	1.537	6.732	657.4***
VaR_{Delta}	0.226	-0.006	9.570	-0.892	0.951	3.637	24.291	14238.2***
$VaR_{Historical}$	0.154	0.001	4.338	-0.811	0.639	1.977	9.015	1457.4***
CR	0.017	0.002	1.192	-0.601	0.198	1.581	10.420	1829.8***
WCR	0.012	0.008	0.521	-0.507	0.106	0.049	6.149	279.2***
LR	0.009	0.004	0.854	-0.619	0.104	1.127	13.925	3499.6***
LTD	0.075	-0.013	15.061	-0.914	0.735	13.988	266.169	1969886.0***
DPP	0.673	1.000	1.000	0.000	0.470	-0.736	1.541	120.7***
ROA	0.315	0.125	26.751	-8.875	1.809	4.700	73.790	143426.9***
TOBINQ	0.022	0.005	2.300	-0.563	0.195	3.443	34.730	29606.8***
GIA	1.593	0.046	706.716	-110.425	27.960	23.727	601.519	101384.0***
GIS	0.303	0.210	3.468	-0.574	0.439	2.615	13.710	3995.6***
GII	0.220	0.144	3.255	-0.982	0.370	3.132	21.439	10665.5***
COVID	0.148	0.000	1.000	0.000	0.356	1.981	4.924	545.5***
SD	2.312	2.164	6.049	1.105	0.692	1.042	4.648	198.5***

Note: Sign *** indicates 1% significance level.

5.2. Correlation Analysis and VIF Analysis

The correlation matrix and *VIF* analysis results for the explanatory variables are presented in Table 4. According to the correlation matrix, ρ=-0.438 between *CR* and *LR* is the highest correlation observed among the explanatory variable pairs. This variable pair is followed by *GIS* and *GII* with ρ=0.302. The absence of any pair of independent variables with ρ>0.75 or ρ<-0.75 indicates that the variables in the data set can be included in the same regression models and will not cause multi-collinearity. The findings of the *VIF* analysis also support the results of the correlation analysis. The *VIF* analysis results show that *LR* has the highest *VIF* value (1.874). The fact that all independent variables have *VIF* values considerably smaller than the critical value of 4 indicates that the explanatory variables will not cause deviations in the model due to multi-collinearity.

Table 4. Testing for Multi-Collinearity

Correlation Matrix											
Variables	*CR*	*WCR*	*LR*	*LTD*	*DPP*	*ROA*	*TOBINQ*	*GIA*	*GIS*	*GII*	*SD*
CR	1.000										
WCR	0.179***	1.000									
LT	-0.438***	0.196***	1.000								
LTD	0.259***	-0.052	0.262***	1.000							
DPP	0.091***	-0.018	-0.078**	0.046	1.000						
ROA	0.062	-0.065*	-0.166***	0.015	0.063	1.000					
TOBINQ	-0.015	-0.011	-0.060	-0.093***	0.019	0.066*	1.000				
GIA	0.015	-0.006	0.028	0.038	0.025	-0.018	-0.031	1.000			
GIS	0.019	0.148***	-0.035	-0.055	-0.099**	0.074*	0.092**	-0.038	1.000		
GII	-0.010	-0.101***	0.031	0.016	-0.121***	-0.013	-0.072*	-0.003	0.302***	1.000	
SD	-0.028	0.033	0.030	-0.034	-0.313***	-0.003	0.141***	0.032	0.241***	0.097***	1.000
Variance Inflation Factor											
Variables	*CR*	*WCR*	*LR*	*LTD*	*DPP*	*ROA*	*TOBINQ*	*GIA*	*GIS*	*GII*	*SD*
R^2	0.445	0.239	0.466	0.308	0.122	0.046	0.051	0.008	0.189	0.140	0.162
VIF	1.803	1.313	1.874	1.445	1.139	1.048	1.054	1.008	1.233	1.163	1.193

Note: Signs ***, **, and * indicate 1%, 5%, and 10% significance levels respectively.

5.3. Panel Cross-section Dependency and Slope Homogeneity Test Results

As a result of the Breusch ve Pagan (1980) *LM*, Pesaran (2004) CD_{LM}, and Pesaran, Ullah and Yamagata (2008) LM_{adj} tests, the null hypothesis can not be rejected for the variables *LTD* and *GIA*, while it is rejected for all other variables. The results of the *LM*, CD_{LM} and LM_{adj} tests reveal that the variables *LTD* and *GIA* do not contain horizontal cross-section dependence, while all other variables contain. As a result of the Pesaran and Yamagata (2008) $\tilde{\Delta}$ ve $\tilde{\Delta}_{adj}$ tests, the null hypothesis is rejected for *WCR*, *LR*, *ROA*, and *GII*, but can not be rejected for all other variables. The results of the $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ tests reveal that the slope coefficients of *WCR*, *LR*, *ROA*, and *GII* are heterogeneous, while the slope coefficients of all other variables are homogeneous.

Table 5. Testing for Cross-section Dependency and Slope Homogeneity

Variables/Tests	Cross-section Dependency Tests			Slope Homogeneity Tests	
	LM	CD_{LM}	LM_{adj}	$\tilde{\Delta}$	$\tilde{\Delta}_{adj}$
$VaR_{MonteCarlo}$	2541.862***	91.52365***	91.04288***	-1.660	-1.761
$VaR_{Bootstrap}$	2282.179***	80.92213***	80.44136***	-2.963	-3.143
VaR_{Delta}	424.1677***	5.069126***	4.588357***	-1.853	-1.966
$VaR_{Historical}$	2039.331***	71.00789***	70.52712***	-2.200	-2.334
CR	360.7585***	2.480454**	1.999685**	-0.507	-0.538
WCR	375.9683***	3.101392***	2.620622***	5.760***	6.110***
LR	563.5896***	10.76100***	10.28023***	1.837**	1.948**
LTD	271.9075	-1.146872	-1.627641	0.190	0.202
ROA	1709.520***	57.54341***	57.06264***	2.610***	2.768***
TOBINQ	1468.489***	47.70338***	47.22261***	-1.368	-1.451
GIA	318.3315	0.748381	0.267612	-2.250	-2.386
GIS	2752.625***	100.1280***	99.64722***	-1.954	-2.072
GII	1042.976***	30.33188***	29.85111***	3.519***	3.733***
SD	2909.272***	106.5231***	106.0423***	-0.789	-0.837
Null hypothesis	H_0: No cross-section dependence			H_0: No heterogeneity in slope coefficients	

Note: Signs ***, and ** indicate 1%, and 5% significance levels respectively.

5.4. Panel Unit Root Test Results

In line with the findings of the *LM*, CD_{LM}, LM_{adj}, $\tilde{\Delta}$, and $\tilde{\Delta}_{adj}$ tests, Levin, Lin and Chu (2002) *LLC* test were performed testing the stationarity of *LTD* and *GIA*, and the Pesaran (2007) CIPS test were performed testing the stationarity of all the other variables. Panel unit root tests results are presented in Table 6.

Table 6. Panel Unit Root Testing

First generation panel unit root test: Levin, Lin & Chu (2002) *LLC*				
Models	Constant		Constant and trend	
Variables	Statistic		Statistic	
LTD	-20.3248***		-19.2939***	
GIA	-16.0474***		-11.3857***	
Second generation panel unit root test: Pesaran (2007) *CIPS*				
Models	Constant		Constant and trend	
Variables	*CIPS*	*Truncated CIPS*	*CIPS*	*Truncated CIPS*
$VaR_{MonteCarlo}$	-6.75038***	-5.80816***	-6.53673***	-5.79590***
$VaR_{Bootstrap}$	-7.03766***	-6.06575***	-6.89263***	-6.16151***
VaR_{Delta}	-6.84963***	-5.99434***	-6.75418***	-6.13349***
$VaR_{Historical}$	-6.42313***	-5.57414***	-6.26748***	-5.66403***
CR	-5.23810***	-4.93487***	-5.25035***	-5.06174***
WCR	-5.30735***	-4.82657***	-5.30422***	-4.86886***
LR	-5.30640***	-5.00360***	-5.69359***	-5.26412***
ROA	-4.84223***	-4.72741***	-5.53204***	-5.16135***
TOBINQ	-5.12045***	-4.96622***	-5.15426***	-4.98869***
GIS	-3.11699***	-3.10984***	-2.99992***	-2.99300***
GII	-4.095E+16***	-2.55993***	-1.695E+16***	-3.08509***
SD	-3.70358***	-3.70358***	-3.76492***	-3.76492***
Critical values for *CIPS* and *Truncated CIPS*				
Significance level	Constant		Constant and trend	
%1	-2.35	-2.35	-2.86	-2.86
%5	-2.18	-2.18	-2.69	-2.69
%10	-2.09	-2.09	-2.60	-2.60
Null hypothesis		H_0: No stationarity.		

Note 1: Lag lengths in the tests were determined using the Schwarz Info Criterion.
Note 2: Sign *** indicates 1% significance level.

The outcomes of the *LLC* and *CIPS* tests indicate that the null hypothesis is rejected for all variables in both the models with constant and the models with constant and trend. The *LLC* and *CIPS* tests results indicate that all dependent and independent variables are stationary at level.

5.5. Diagnostic Test Results

Table 7 contains the diagnostic test results for serial correlation and heteroskedasticity assumptions in the models. Baltagi and Li (1991) LM_p, Born and Breitung (2016) LM_p^*, and Breusch and Pagan (1979) LM_h tests reject the null hypothesis for all models. LM_p, LM_p^*, and LM_h results show that all models contain autocorrelation and heteroskedasticity at 1% significance level.

Table 7. Diagnostic Test Results

Tests/Models	MonteCarlo	Bootstrap	Delta	Historical
Baltagi ve Li (1991) LM_p	46.20542***	78.285230***	60.500080***	88.303600***
Born ve Breitung (2016) LM_p^*	60.76060***	97.018430***	77.049050***	108.161900***
Breusch ve Pagan (1979) LM_h	54.93021***	58.357410***	227.913500***	91.510570***
Null hypothesis	H_0: No serial correlation yoktur.		H_0: No heteroskedasticity yoktur.	

Not: Sign *** indicates 1% significance level.

Since the presence of autocorrelation and heteroskedasticity in panel regression models can lead to inconsistencies and high deviations in the analysis, the Cross-section SUR (PCSE) robust estimator developed by Beck and Katz (1995) is used in estimations.

5.6. Estimator Specification Tests

Finally, Table 8 presents the results of the *F* test, which is used to examine the variation in the fixed parameter in the models, and the Breusch and Pagan (1980) *LM* and Honda (1985) tests, which are used to determine whether there are random effects in the model.

Table 8. Estimator Specification Tests

Tests	Models	MonteCarlo	Bootstrap	Delta	Historical
F Test	Group fixed effets	0.1786	0.1580	0.3160	0.3031
	Time fixed effets	26.7803***	22.6855***	1.5870**	18.8463***
	Two way fixed effets	14.0221***	11.8892***	0.9799	9.9977***
Breusch and Pagan (1980) *LM* Test	Group random effets	10.5987***	10.4750***	6.1724**	7.6711***
	Time random effets	1980.64***	1682.5290***	4.0194**	1338.09***
	Two way random effets	1991.24***	1693.0040***	10.1918***	1345.76***
Honda (1985) Test	Group random effets	-3.2556	-3.2365	-2.4844	-2.7697
	Time random effets	44.5044***	41.0186***	2.0049**	36.5799***
	Two way random effets	29.1674***	26.7160***	-0.3391	23.9075***
Null hypothesis	Group fixed/random effets	H_0: While there is a cross-section effect, there is no time effect.			
	Time fixed/random effets	H_0: While there is a time effect, there is no cross-section effect.			
	Two way fixed/random effets	H_0: No cross-section or time effect.			

Note: Signs ***, and ** indicate 1%, and 5% significance levels, respectively.

The *F* test results show that for all models, group fixed effects statistics are insignificant while time fixed effects statistics are significant. The *F* test results indicate that all models have one-way time fixed effects. The *LM* test indicates that all models contain two-way random effects and the Honda test indicates that all models contain one-way time random effects. According to Baltagi (2014), in panel data analysis, the choice of the appropriate model depends on the nature of the dataset. The pooled model is suitable when there is no distinction between countries or firms in the dataset. The random effects model is preferred when countries or firms are randomly selected from a large population. Conversely, the fixed effects model is more appropriate when the dataset focuses on a specific set of countries or firms, and the analysis aims to capture the behavior of this particular group. Given that the dataset concentrates on non-financial companies within the BIST 100 Index in Türkiye, the one-way fixed effects model is employed in the estimations in line with the *F* test results and Baltagi (2014) approach.

5.7. Panel Regression Results

Table 9 presents the estimation outcomes of the panel regression model in equations (1), which is developed to determine the relationship between *VaR* calculated by Monte-Carlo simulation, Bootstrap, Delta and Historical simulation methods and financial decisions.

Table 9. Panel Regression Results

Models	MonteCarlo		Bootstrap		Delta		Historical	
Dependent Variables	$VaR_{MonteCarlo}$		$VaR_{Bootstrap}$		VaR_{Delta}		$VaR_{Historical}$	
Independent Variables	Coef.	t-Statistic	Coef.	t-Statistic	Coef.	t-Statistic	Coef.	t-Statistic
CR	-0.0270	-1.7297*	-0.0064	-0.7546	0.0892	2.5780**	0.1102	4.5041***
WCR	0.0264	0.9749	-0.0744	-5.9976***	-0.0967	-1.3883	0.0854	2.4721**
LR	0.1496	4.2277***	0.2723	17.8208***	0.0812	1.0789	0.4126	8.8743***
LTD	0.0003	0.0730	0.0282	15.4027***	-0.0697	-9.2898***	0.0225	3.0546***
DPP	0.0789	14.2605***	0.0968	33.3547***	0.0844	5.6159***	0.0641	8.3571***
ROA	-0.0194	-17.1353***	-0.0332	-36.4389***	0.0114	2.9158***	-0.0533	-25.4893***
TOBINQ	-0.1521	-10.2060***	-0.3865	-35.5895***	0.0309	0.8144	-0.3628	-13.4942***
GIA	0.0006	9.6164***	0.0008	7.3495***	-0.0008	-3.3058***	-0.0001	-1.1415
GIS	-0.0785	-8.7412***	-0.1261	-19.4374***	0.0102	0.4363	-0.1639	-13.3561***
GII	0.0287	5.0236***	0.0355	8.9777***	0.0752	4.1334***	-0.0293	-3.6714***
COVID	-0.0141	-0.4206	0.0971	8.4843***	-0.0897	-2.1199**	0.0106	0.2595
SD	0.2648	24.9242***	0.2860	67.3596***	0.0289	2.3830**	0.3098	36.9060***
C	-0.5776	-19.7078***	-0.5797	-60.8995***	0.0832	1.9930**	-0.5389	-21.1808***
R^2	0.6114		0.8993		0.2122		0.7336	
Adjusted R^2	0.6043		0.8975		0.1979		0.7288	
F-Statistic	86.6505***		491.9297***		14.8399***		151.6776***	
Prob(F-Statistic)	0.0000		0.0000		0.0000		0.0000	
Durbin-Watson Stat.	2.0120		2.0124		2.0108		2.0142	
Null hypothesis			H_0: Financial decisions have no effect on *VaR*.					

Note 1: Panel EGLS (Period weights) method and Period SUR (PCSE) robust estimator were used in all models

Note 2: Signs ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

The results of the panel regression analysis show that the *F* probability values, which express the significance of the models as a whole, are lower than 0.01 in all models and therefore all models are statistically significant at the 1% significance level. This finding indicates that the null hypotheses tested by equation (1) is rejected at 1% significance level for all models. Therefore, it is safe to say that financial decisions have statistically significant effects on the changes in the *VaR* calculated by different methods in non-financial BIST 100 Index companies. F-statistic values of the models can be compared to determine which *VaR* variable is more successfully explained by financial decisions. Model Bootstrap has the highest F-statistic value (491.93). In this sense, model Bootstrap is followed by model Historical (151.68), model MonteCarlo (86.65) and model Delta (14.84). The R^2 values of the models are also consistent with the F-statistic values. The R^2 values indicate that the independent variables in the models as a whole can explain 89.93% of the changes in $VaR_{Bootstrap}$, 73.36% of the changes in $VaR_{Historical}$, 61.14% of the changes in $VaR_{MonteCarlo}$ and 21.22% of the changes in VaR_{Delta} for non-financial BIST100 Index companies. The fact that the Durbin-Watson statistics are close to 2 for all models indicates that the autocorrelation problem in the models have been effectively eliminated by the robust estimators. This suggests that serial-correlation among the error terms has been mitigated, thereby bolstering the reliability of the regression outcomes.

The results of the analysis show that the effects of *CR*, which represents working capital financing decisions in the models, on $VaR_{MonteCarlo}$, VaR_{Delta} and $VaR_{Historical}$ are statistically significant at 10%, 5% and 1% significance levels, respectively. The effects of *WCR*, which represents working capital investment decisions, on $VaR_{Bootstrap}$ and $VaR_{Historical}$ are statistically significant at 1% and 5% significance levels, respectively. Capital structure decisions variables also found to have significant effects on *VaR*. Findings indicate that the effects of *LR* on $VaR_{MonteCarlo}$, $VaR_{Bootstrap}$ and $VaR_{Historical}$ are statistically significant at 1% significance level, while the effects of *LTD* on $VaR_{Bootstrap}$, VaR_{Delta} and $VaR_{Historical}$ are statistically significant at 1% significance level. The dummy variable representing the dividend pay-out policy is statistically significant at the 1% significance level in all models. Financial performance indicators *ROA* and *TOBINQ* are among the important variables to explain the *VaR*. The effects of *ROA* is statistically significant at the 1% significance level in all models, while the effects of *TOBINQ* on $VaR_{MonteCarlo}$, $VaR_{Bootstrap}$ and $VaR_{Historical}$ are statistically significant at the 1% significance level. Among the variables representing the growth policies of companies, the effects of *GIA* on $VaR_{MonteCarlo}$, $VaR_{Bootstrap}$ and VaR_{Delta} are statistically significant at the 1% significance level, the effects of *GIS* on $VaR_{MonteCarlo}$, $VaR_{Bootstrap}$ and $VaR_{Historical}$ are statistically significant at the 1% significance level, and finally, the effects of *GII* is statistically significant at the 1% significance level in all models. The effects of the dummy variable representing the Covid-19 pandemic on the changes in the *VaR* are statistically significant at the 1% significance level for $VaR_{Bootstrap}$ and at the 5% significance level for VaR_{Delta}. The standard deviation variable included in the models as a control variable is statistically significant at the 1% significance level in all models. These findings suggest that various financial decisions, capital structure, dividend policy, financial performance indicators, growth policies, and the impact of the Covid-19 pandemic play significant roles in explaining changes in *VaR* across different methodologies and scenarios.

Table 10. Summary of The Results

Models	MonteCarlo	Bootstrap	Delta	Historical
Variables	$VaR_{MonteCarlo}$	$VaR_{Bootstrap}$	VaR_{Delta}	$VaR_{Historical}$
CR	Negative	Insignificant	Positive	Positive
WCR	Insignificant	Negative	Insignificant	Positive
LR	Positive	Positive	Insignificant	Positive
LTD	Insignificant	Positive	Negative	Positive
DPP	Positive	Positive	Positive	Positive
ROA	Negative	Negative	Positive	Negative
TOBINQ	Negative	Negative	Insignificant	Negative
GIA	Positive	Positive	Negative	Insignificant
GIS	Negative	Negative	Insignificant	Negative
GII	Positive	Positive	Positive	Negative
COVID	Insignificant	Positive	Negative	Insignificant

Table 10 summarizes the direction of the effects of financial decisions on *VaR*. The results reveal that the effects of firm managements' decisions regarding investment and growth policy, financing policy and dividend pay-out policy on *VaR* vary depending on the *VaR* calculation method. According to the results of the model Bootstrap, which demonstrates the highest efficacy based on F-statistics and R^2 values, certain trends emerge: (1) increases in financial performance and sales growth, as well as decisions to augment working capital investments, contribute to a decrease in firms' *VaR*; (2) conversely, decisions by firm management to borrow, distribute cash dividends, and increase investments tend to elevate firms' *VaR*. The findings from the model Bootstrap generally align with existing finance literature, particularly regarding the effects of financing policies, dividend pay-out policies, sales policies, and financial performance on *VaR*. The findings of model MonteCarlo, model Bootstrap and model Historical are significantly consistent in terms of the effects of financing policies, dividend pay-out policies, sales policies and financial performance on firms' *VaR*. However, there are discrepancies in the effects of short-term investments and working capital financing policies on *VaR* across the models developed.

These results underscore the nuanced relationship between financial decisions and *VaR*, emphasizing the importance of considering specific methodologies and contexts in analyzing their impact. The consistency across certain models suggests robustness in certain findings, while variations highlight the complexity inherent in assessing risk in financial decision-making.

6. CONCLUSIONS AND POLICY RECOMMENDATIONS

The current study aims to reveal the imcapt of financial decisions on the firms' *VaR* through various *VaR* calculation methods. The analysis utilizes data from non-financial firms listed in the BIST 100 Index, the Turkish stock market, spanning from January 2010 to June 2023. The data set is a balanced panel data constructed using semi-annual financial statement and stock market data. *VaR* calculated through Monte-Carlo simulation, Bootstrap, Delta and Historical simulation methods, commonly employed in *VaR* calculations, are included as dependent variables in the econometric models. Explanatory variables encompass three basic components of financial management: investment and growth policy, financing policy and dividend pay-out policy. Financial decisions are analyzed through financial ratios of companies in line with the basic principles of corporate finance. A dummy variable is used to reveal the effects of the Covid19 pandemic on companies' *VaR*. Within the scope of the study, a total of four panel regression models are developed to explore the relationship between financial decisions and *VaR*. Prior to estimating the models, various econometric tests are conducted to assess multicollinearity, horizontal cross-section dependence, homogeneity, stationarity, autocorrelation, and heteroskedasticity assumptions. The presence of time and/or group fixed effects and/or random effects in the models is examined using *F*, *LM*, and Honda tests to determine the most appropriate estimator. Robust estimators developed by Beck and Katz (1995) are employed to overcome identified autocorrelation and heteroscedasticity issues within the models.

All panel regression models constructed in the analyses demonstrate statistical significance. Consequently, the financial decisions of non-financial firms listed in the BIST 100 Index are found to significantly influence the changes in *VaRs* calculated using various methods. The results indicate that the effects of management decisions regarding long and short-term investments and growth, capital structure, and dividend payout on *VaR* vary depending on the *VaR* calculation method. Notably, financial decisions exhibit a stronger explanatory power for changes in *VaR* calculated via the Bootstrap method compared to other methods. Conversely, the Delta method shows the least successful explanation by financial management decisions. While model Bootstrap reveals findings aligning with existing finance literature, model Delta presents findings that contradict prevailing finance literature. Moreover, the Bootstrap method emerges as a more reliable approach for *VaR* calculations compared to other methods, highlighting its potential for enhancing risk management practices in financial decision-making. Thus, it is imperative to consider the implications of model Bootstrap's findings for various stakeholders, including financial managers, stakeholders, investors, investment consultants, and researchers.

The results obtained from the Bootstrap model indicate that increases in working capital investments lead to a significant reduction in *VaR*. Conversely, the MonteCarlo model findings suggest that utilizing long-term financing options for working capital financing significantly decreases *VaR*. Therefore, prudent financing policies and flexible investment strategies in working capital management among non-financial BIST 100 Index firms are anticipated to decrease their *VaR*. Across the MonteCarlo, Bootstrap, and Historical models, it is evident that management decisions regarding borrowing significantly impact *VaR*. Specifically, increases in leverage and long-term debt ratios are associated with elevated *VaR* levels. These findings suggest that changes in the capital structure, as suggested by the trade-off theory, result in high levels of debt, where the advantages of tax shield cannot cover the costs of financial distress and bankruptcy, and increases the firm's *VaR*. Consequently, non-financial BIST 100 Index firms opting for internal financing sources over debt financing are expected to reduce their *VaR*. Furthermore, all analyzed models underscore the significant effects of dividend pay-out policies on *VaR*. The decision to distribute cash dividends tends to lead firms towards debt financing, consequently increasing *VaR*. In this context, non-financial BIST100 Index firms are encouraged to decrease their *VaR* by relying on internal financing sources such as auto-financing. The findings from the MonteCarlo, Bootstrap, and Historical models consistently demonstrate that increases in firms' profitability and financial performance correlate with decreased *VaR*. Effective production, cost, pricing, and sales policies that enhance firm profitability play a pivotal role in reducing *VaR*. Moreover, the growth in firms' sales, as highlighted by the MonteCarlo, Bootstrap, and Historical models, negatively impacts *VaR*. This supports the findings on working capital investment policies from the Bootstrap model and the findings on profitability and financial performance from the MonteCarlo, Bootstrap and Historical models. The findings suggest that firms can significantly mitigate *VaR* through investments in production and inventories, along with the implementation of effective production, cost, price, and sales policies. Additionally, the MonteCarlo and Bootstrap models reveal that growth in foreign investments exerts a positive impact on *VaR*, further reinforcing the relationship between capital structure and *VaR*. Lastly, regarding the effects of the Covid19 pandemic, one of the most globally impactful events during the study period, findings indicate its increasing effect on firms' *VaR* due to disruptions in the supply chain, production, distribution, and demand dynamics.

In conclusion, the findings of the analysis offer insightful responses to the research questions, shedding light on the pivotal role of financial decisions in risk management. The empirical evidence reveals that investment and growth policies, financing decisions, and dividend pay-out policies significantly influence firms' potential losses. The discretion exercised by firm management in these areas plays a pivotal role in determining the level of risk exposure faced by the organization. Investment and growth decisions directly impact the scale and scope of operations, affecting the overall risk profile of the firm. Similarly, financing choices influence the capital structure and leverage levels, which in turn affect the firm's vulnerability to financial distress and potential losses. Furthermore, dividend distribution policies reflect management's approach to allocating profits and managing liquidity, which can have implications for the firm's financial health and risk exposure. In essence, the findings underscore the interconnectedness between strategic financial decisions and risk management outcomes. By carefully evaluating and aligning these decisions with the firm's risk appetite and broader objectives, management can effectively mitigate potential losses and enhance the overall resilience and sustainability of the organization. The identification of significant differences between *VaR* methods in terms of corporate finance principles highlights the critical nature of selecting the appropriate *VaR* methodology when crafting risk management strategies. *VaR* serves as a key tool for quantifying and managing potential losses within a firm's portfolio or financial system. The variations observed among *VaR* methods underscore the importance of understanding the underlying assumptions, limitations, and applicability of each approach. Different *VaR* methodologies may utilize distinct statistical techniques, historical data sources, and modeling assumptions, leading to divergent risk estimates and implications for decision-making. Given these differences, the choice of *VaR* method becomes pivotal in accurately assessing and mitigating potential losses. Management must carefully evaluate the suitability of each *VaR* approach based on factors such as the firm's risk profile, business model, regulatory requirements, and market conditions. Ultimately, the selection of the most appropriate *VaR* method should align with the firm's risk management objectives and corporate finance principles. By leveraging the insights provided by robust *VaR* methodologies, firms can enhance their ability to anticipate, monitor, and respond to potential risks effectively, thereby safeguarding their financial stability and resilience in dynamic market environments. The findings of the analysis suggest that the Bootstrap model emerges as the most suitable *VaR* measurement model for non-financial firms operating in Turkey, aligning closely with corporate finance principles. This designation shows the efficacy and reliability of the Bootstrap method in quantifying and managing potential losses within the context of Turkish non-financial firms. The adoption of the Bootstrap model in *VaR* measurement holds significant promise for enhancing risk management practices among non-financial firms in Turkey. By leveraging the robustness and accuracy of the Bootstrap method, firms can develop more effective risk strategies and proactively mitigate potential losses.

The empirical findings generated from the analyses are anticipated to provide valuable guidance for firms' financial management and risk management strategies, thereby enriching the literature by elucidating the role of financial management policies in risk mitigation. The insights gleaned from the study hold potential benefits for a wide array of stakeholders including investors, portfolio managers, investment consultants, researchers, and particularly firm managers. It is crucial to approach the findings of this study with consideration for its limitations regarding cross-sectional and time dimensions. As the study focuses solely on publicly traded non-financial BIST 100 Index companies, generalizing the findings to financial companies may lead to inaccuracies. Additionally, the exclusion of factors beyond financial decisions, represents another important limitation. In future research endeavors, delving into the effects of firms' market performance and macroeconomic factors on Value at Risk on a firm basis would further enrich the literature in this domain. Exploring how market dynamics and broader economic conditions influence firm base *VaR* can offer deeper insights into risk management practices and inform decision-making processes for firms across various industries and sectors. Such investigations would not only advance academic discourse but also provide practical implications for real-world risk management strategies.

The study does not necessitate Ethics Committee permission.

The study has been crafted in adherence to the principles of research and publication ethics.

The author declares that there exists no financial conflict of interest involving any institution, organization, or individual(s) associated with the article.

The entire work of the study was carried out by its only, stated author.

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