Araştırma Makalesi / Research Article

Predicting Market Sensitivity: The Role of Board Structure in the Beta Coefficient of Software Companies on the NASDAQ Global Select Market

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Abstract

This study examines how board structure influences market sensitivity, measured by Beta, in software companies listed on the NASDAQ Global Select Market. Focusing on governance metrics such as board size, meeting frequency, and executive compensation, the research analyzes their impact on Beta from 2014 to 2023. Machine learning models, including Decision Trees and Bagging Classifiers, evaluate this relationship, using accuracy, precision, recall, and F1 scores. Findings suggest that governance factors significantly affect market sensitivity, offering valuable insights for corporate leaders and investors managing firm risk in volatile sectors like software.

Keywords: *Beta Coefficient, Corporate Governance, Market Sensitivity Prediction, Board Structure*

JEL Kodları: *G32, C45, C53*

Piyasa Duyarlılığını Tahmin Etmek: NASDAQ Global Select Market'teki Yazılım Şirketlerinin Beta Katsayısında Yönetim Kurulu Yapısının Rolü

Öz

Bu çalışma, NASDAQ Global Select Market'te listelenen yazılım şirketlerinde yönetim kurulu yapısının Beta ile ölçülen piyasa duyarlılığını nasıl etkilediğini incelemektedir. Yönetim kurulu büyüklüğü, toplantı sıklığı ve yönetici ücretleri gibi yönetişim ölçütlerine odaklanan araştırma, bunların 2014-2023 yılları arasında Beta üzerindeki etkisini analiz etmektedir. Karar Ağaçları ve Torbalı Sınıflandırıcılar dahil olmak üzere makine öğrenimi modelleri, doğruluk, kesinlik, geri çağırma ve F1 puanlarını kullanarak bu ilişkiyi değerlendirmektedir. Bulgular, yönetişim faktörlerinin piyasa duyarlılığını önemli ölçüde etkilediğini ve yazılım gibi değişken sektörlerde firma riskini yöneten kurumsal liderler ve yatırımcılar için değerli içgörüler sunduğunu göstermektedir.

Anahtar Sözcükler: *Beta Katsayısı, Kurumsal Yönetim, Piyasa Duyarlılığı Tahmini, Yönetim Kurulu Yapısı*

JEL Codes**:** *G32, C45, C53*

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1. Introduction

Market sensitivity, often measured by the Beta coefficient, is a fundamental concept in finance that reflects how a company's stock price responds to movements in the broader market. This measure of systematic risk is particularly crucial for investors and corporate managers in industries characterized by high volatility, such as the software sector. Understanding the determinants of Beta can provide valuable insights into a firm's risk profile and inform investment decisions (Shanthi and Thamilselvan, 2019).

Corporate governance, particularly the structure of a company's board of directors, plays a significant role in shaping strategic decisions and risk management practices (Berglund, 2020). The composition of the board, including factors such as size, diversity, and independence, has been shown to influence a firm's performance and its exposure to market risks (Younas et al., 2019). Effective corporate governance mechanisms may mitigate agency problems, aligning management actions with shareholder interests, which is essential in maintaining stability in high-risk environments.

The technology industry, known for rapid technological advancements and intense competition, presents unique challenges in managing market sensitivity (Enalpe, 2022). Firms in this sector are more susceptible to shifts in investor sentiment, which can drive significant fluctuations in stock prices. While there is extensive research on corporate governance and firm performance, the specific impact of board structure on Beta in software companies remains underexplored.

Previous research on corporate governance has typically focused on its effect on overall firm performance, such as profitability or shareholder value. For instance, Mishra and Kapil, (2018) found that board size and independence positively influence firm performance in Indian companies. Similarly, Younas et al., (2019) highlighted the role of independent directors in curbing excessive risk-taking behavior in firms. However, these studies primarily address performance metrics and do not delve into how board characteristics impact market sensitivity measures like Beta.

Understanding this relationship is important, as board characteristics can significantly influence a company's risk profile. A larger board may offer more diverse perspectives and stronger oversight, potentially reducing a firm’s exposure to market volatility (Yasser et al., 2017). Conversely, smaller boards, while potentially more agile in decision-making, may lack the necessary checks and balances, which could increase market sensitivity (Ongore et al., 2015). Additionally, board diversity, including gender diversity, has been linked to better firm performance, which may also affect risk-taking behavior and market sensitivity (Gerged et al., 2023).

The role of executive compensation in influencing firm risk is another relevant consideration. Compensation structures that align executive incentives with shareholder interests may encourage risk-taking that enhances firm value. However, excessive risk-taking could increase a firm's market sensitivity, particularly in volatile industries such as software (Rama Iyer et al., 2020).

Machine learning techniques have emerged as powerful tools for analyzing complex relationships between governance variables and market outcomes. Studies such as Turel et al., (2019) have used advanced analytical methods to assess the impact of IT governance on firm performance, suggesting that similar approaches could yield valuable insights into how board structure affects Beta in the software industry.

This study aims to address a gap in the existing literature by examining the influence of board structure on the market sensitivity (Beta) of software companies listed on the NASDAQ Global Select Market. Through the investigation of key governance variables, including board size, meeting frequency, and executive compensation, the research seeks to assess how these factors contribute to the prediction of Beta. The use of machine learning models enables a detailed and data-driven exploration of the complex relationships between board structure and market sensitivity.

Understanding the factors influencing stock volatility and Beta is crucial for risk management and predicting market behavior. Tang et al., (2013) emphasized that changes in a firm's market listing can significantly alter volatility and bid-ask spreads, highlighting how internal and external factors influence market sensitivity. This underscores the necessity of examining the variables that affect Beta, especially in sectors such as technology, where volatility plays a prominent role.

The significance of this research lies in its potential contributions to both academic knowledge and practical applications. For academics, the study offers empirical evidence on the relationship between board structure and market sensitivity in the software industry, an area that has received limited attention. For practitioners, understanding these dynamics can inform corporate governance practices and risk management strategies. Investors may benefit from insights into how governance characteristics influence a firm's Beta, aiding in portfolio construction and risk assessment.

2. Literature Review

Understanding the factors influencing a firm's Beta is essential for assessing its market risk and making informed investment decisions. Beta, as a measure of a stock's sensitivity to market movements, plays a pivotal role in portfolio management and risk assessment (Fama and French, 1992). Despite the extensive use of Beta in financial analysis, the determinants of Beta, particularly non-financial factors such as corporate governance attributes, have yet to be fully explored.

Corporate governance mechanisms, especially board structure, are integral to firm performance and risk management practices. The board of directors serves as a critical link between shareholders and management, overseeing strategic decisions and monitoring managerial actions (Jensen and Meckling, 1976). Several studies have explored how board characteristics influence firm risk profiles. Yermack, (1996) found that smaller boards are associated with higher firm valuation, suggesting that board size may affect monitoring efficiency and decision-making processes. Conversely, larger boards might offer broader expertise and perspectives, potentially enhancing risk management capabilities.

Empirical evidence on the relationship between board independence and risk presents mixed results. Wang and Hsu, (2013) suggested that higher board independence enhances monitoring functions, leading to reduced firm risk. In contrast, Chaudhary, (2021) found that in the Indian context, an increase in independent directors was positively associated with stock return volatility, indicating that excessive independence might impede strategic agility and increase exposure to market volatility.

Gender diversity on boards has also been examined for its impact on firm risk. Sherif et al., (2024) investigated the association between internal corporate governance mechanisms and stock price volatility in Egypt, finding that board size and the frequency of board meetings negatively influence volatility, whereas board independence had a positive impact. Their study implies that diverse perspectives can contribute to more comprehensive decision-making processes, potentially affecting stock return volatility.

The relationship between corporate governance and Beta has received limited empirical attention. Li et al., (2024) analyzed the relationship between corporate governance and capital market risk in China, finding that corporate governance decreases capital market risk using new risk measurement at the firm level. Their further analysis indicated that this effect is more pronounced in private companies, companies with higher indebtedness, and companies with lower concentration of power. Similarly, Koerniadi et al., (2014) found that firms with robust governance mechanisms tend to exhibit lower levels of risk, suggesting that effective governance can lead to more prudent decision-making, thereby affecting the firm's Beta.

Tan and Liu, (2016) examined the effect of CEO power and board characteristics on idiosyncratic volatility, reporting that stronger managerial power is associated with lower volatility. Although their focus was on idiosyncratic rather than systematic risk, their findings imply that governance structures may have a broader impact on various dimensions of firm risk, including Beta. Tadele et al., (2022) also investigated the impact of internal and external governance attributes on firm risk, finding that board structure and entrenchment factors have a differential impact on firms' jump and volatility risks.

Despite these insights, direct studies linking board structure to Beta are scarce. Most existing research focuses on overall firm risk or specific risk measures without isolating the effect on Beta. For instance, Suleymanov et al., (2024) investigated asymmetric stochastic volatility and leverage effects within the Nasdaq-100 index, revealing dense clustering of volatility both for the index and individual stocks. They observed that volatility is continuous but has a predictable impact on variability, with most stocks exhibiting leverage effects and asymmetric relationships.

The software industry, characterized by high growth potential and innovation-driven dynamics, often experiences elevated market sensitivity and volatility (Maheshwari and Naik, 2024). Software companies face unique risks related to technological changes, intellectual property issues, and rapid shifts in consumer preferences (Giot, 2005). These factors can lead to higher Betas compared to firms in more stable industries. Research on the determinants of Beta within the software sector is limited.

Lamba et al., (2024) highlighted the necessity of investigating the predictive capabilities of the Nasdaq Composite Index due to its significant influence on the global economy. Their study utilized time series-based predictive analysis to forecast the performance of an index traded on a national stock market, employing multivariate algorithms such as LSTM and Bidirectional-LSTM. The findings indicate that advanced predictive models can enhance understanding of market dynamics in the technology sector.

Arisoy et al., (2015) proposed a volatility-based CAPM that incorporates changes in aggregate volatility expectations, demonstrating that traditional models may not fully capture the nuances of Beta dynamics. This suggests that innovative modeling techniques, including machine learning, could provide deeper insights into how board structure variables interact with market factors to influence Beta. Li et al., (2024) support this notion by emphasizing the role of corporate governance in reducing capital market risk, which may, in turn, affect Beta.

Furthermore, studies have explored the impact of ownership structure on firm performance and risk. Yuan et al., (2023) investigated the moderating effect of board activeness on the relationship between corporate ownership structure and firm performance, revealing that board dynamics play a significant role in influencing risk profiles. Similarly, Goel et al., (2022) examined whether board composition is effective in improving firm performance across different levels, finding that board size positively affects performance across all quantiles, while independent directors negatively impact performance.

In emerging markets, Sherif et al., (2024) found that ownership concentration negatively influences stock price volatility, and managerial ownership also showed a negative influence. Their findings suggest that internal corporate governance mechanisms can significantly affect firm risk, highlighting the importance of considering market-specific factors when examining the relationship between board structure and Beta.

The use of machine learning models has been proposed to enhance the understanding of complex interactions between board structure variables and market risk factors. Machine learning techniques allow for the analysis of large datasets and sophisticated algorithms to uncover hidden patterns that could improve predictions of market sensitivity (Arisoy et al., 2015). This approach could be particularly valuable in the software industry, where rapid technological advancements and market dynamics require more nuanced analysis.

This study aims to make a contribution to the existing body of knowledge by examining this relationship and employing machine learning techniques to capture the complexity of the interactions. The objective is to provide valuable insights for investors, corporate managers, and policymakers concerned with market sensitivity and risk management in the technology sector.

3. Methodology

3.1. Dataset and Variables

The dataset used in this study consists of financial and governance data for software companies listed on the NASDAQ Global Select Market. The data spans from 2014 to 2023, sourced from the Eikon Database, with a yearly interval. It includes vital corporate governance variables related to board structure and financial performance. As in Table 1, the primary dependent variable, Beta, measures the volatility of each company's stock relative to the overall market. Several independent variables representing board structure and financial performance are considered, including:

Table 1

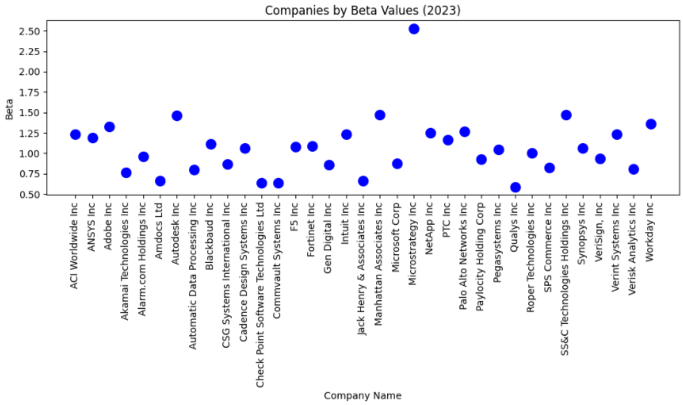
Description of Variables

Variable	Description
Beta	Stock volatility relative to the market
WACC Equity Risk Premium, (%)	Weighted average cost of capital's equity risk
Number of Board Meetings	Total number of board meetings held each year
Board Size	Number of directors on the board
Female on Board	Binary variable for the presence of female directors
To. Senior Exec. Compensation (USD)	Total compensation for senior executives
Highest Remuneration Package (USD)	Highest compensation package for any executive
Board Member Compensation (USD)	Compensation for board members
Close Price	Stock closing price at year-end
Book Value Per Share (USD)	Book value of the company's stock per share
WC/Sales	Working capital as a percentage of sales
Corporate Gov. Board Committee	Binary variable indicating the presence of committee
Nomination Board Committee	Binary variable indicating the presence of committee
Audit Board Committee	Binary variable indicating the presence of committee
Compensation Board Committee	Binary variable indicating the presence of committee
CEO Board Member	Binary variable indicating whether CEO is on board
CSR Sustainability Committee	Binary variable indicating the presence of committee

These variables were selected based on their relevance to corporate governance literature, which suggests that elements such as board composition, executive compensation, and committee structure may influence firm performance and risk-taking behavior.

Figure 1

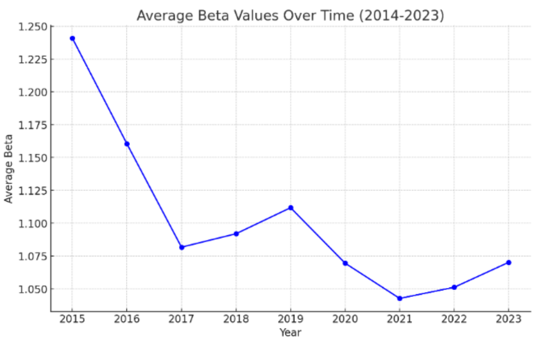
Beta Values of Companies



Beta, a measure of stock volatility relative to the market, is the critical variable for clustering and subsequent analysis. As shown in Figure 1, the Beta values for the companies in the dataset range between approximately 0.50 and 2.00, indicating varying levels of market sensitivity.

Figure 2

Average Beta Values



The analysis of beta values across the ten years shows how software companies' market volatility fluctuated in response to broader market conditions. As shown in the Figure 2, the average Beta for these companies has varied significantly over the years, with peaks occurring in 2019 and 2023, suggesting heightened market volatility during these periods.

The spikes in Beta during 2019 and 2023 may reflect external market factors, such as technological shifts, investor sentiment, or economic downturns, which affect the software industry more acutely than other sectors. These results highlight the inherent volatility of the software sector, where companies are more exposed to rapid market changes.

3.2. Data Preprocessing

Due to missing values in the dataset, we employed interpolation to estimate these missing data points. Interpolation is a widely accepted method for handling missing data in time series analysis, as it utilizes adjacent observations to estimate missing values based on temporal continuity (Enders, 2010). This approach helps maintain the integrity of the dataset and preserves underlying trends, which is crucial for accurate financial analysis (Tsay, 2005).

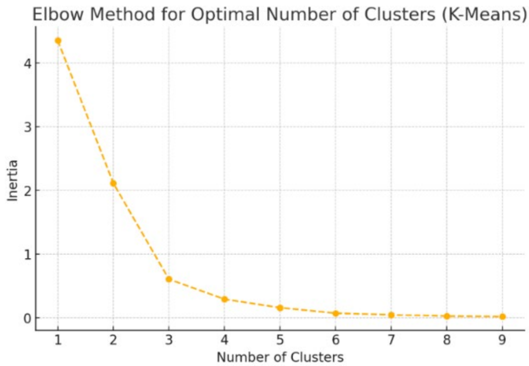
3.3. Clustering Analysis

In this study, we aimed to cluster software companies based on their Beta values in 2023 to identify patterns in market sensitivity. We utilized the K-Means clustering algorithm, a popular unsupervised method used for data segmentation by assigning data points to clusters based on their distance to centroids (Bhavani and Subhash Chandra, 2023). K-Means' performance heavily depends on selecting the number of clusters (k), a crucial parameter in the algorithm.

To determine the optimal number of clusters, we employed the Elbow Method, which estimates the appropriate value of k by plotting the within-cluster sum of squares against the number of clusters (Cai and Wang, 2020; Pandharbale et al., 2021). As shown in the elbow plot (Figure 3), our analysis revealed a significant decrease in inertia as the number of clusters increased from 1 to 4. Beyond four clusters, the reduction rate slowed considerably, suggesting that four is our dataset's optimal number of clusters.

In addition to K-Means clustering, we applied hierarchical agglomerative clustering to validate our findings. This method treats each data point as an individual cluster at the outset. It successively merges pairs of clusters based on similarity until all data points are grouped into a single cluster (Jin and Xiao, 2013). The process can be visualized using a dendrogram (Figure 4), which provides a hierarchical data structure and aids in determining the number of clusters (Jeantet et al., 2020).

Figure 3
Elbow Method Results



However, traditional hierarchical clustering methods can accumulate errors if data points are incorrectly merged early, leading to less accurate clustering results (Jin and Xiao, 2013). Despite this limitation, the Dendrogram (Figure 4) displayed clear separations between four main clusters, reinforcing the choice of the Elbow Method.

Figure 4
Hierarchical Agglomerative Clustering Results

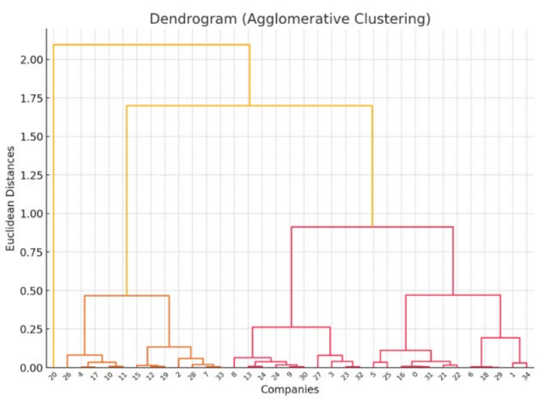


Figure 4. Hierarchical Agglomerative Clustering Results

Based on the Elbow Method and the Agglomerative Clustering results, the decision was made to proceed with four clusters. This approach balances the need for simplicity (fewer clusters) with the desire to capture meaningful distinctions in market volatility among the companies. The four clusters identified in the analysis can be interpreted as follows:

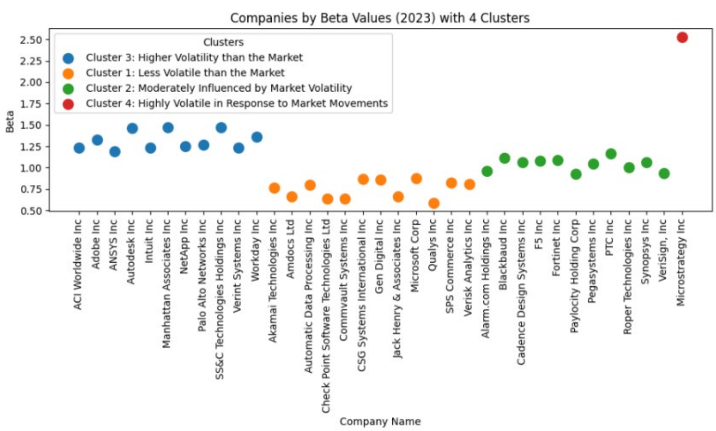
The four clusters represent varying levels of market sensitivity, as outlined below:

- Cluster 1: Less Volatile than the Market – Companies in this cluster exhibited Beta values lower than 1, indicating that they are less sensitive to market fluctuations than the broader market.
- Cluster 2: Moderately Influenced by Market Volatility – Companies in this cluster had Beta values slightly above 1, reflecting a moderate correlation with market movements but without excessive volatility.
- Cluster 3: Higher Volatility than the Market – Companies in this cluster had beta values significantly above 1, showing a tendency for price swings that were more significant than those of the market.
- Cluster 4: Highly Volatile in Response to Market Movements – This group exhibited the highest Beta values, indicating that these companies are susceptible to market changes, experiencing substantial price movements in line with or even exceeding those of the market.

These clusters provide a structured framework for analyzing how corporate governance characteristics, such as board structure and executive compensation, influence a company’s market sensitivity.

Figure 5

Clustered Beta Coefficients of Companies



As in Figure 5, four clusters derived from the Beta values were the dependent variable for subsequent machine learning models. The purpose was to predict a company's membership in one of these clusters based on its governance and financial characteristics. By categorizing companies into distinct volatility groups, the study aims to identify governance practices that may mitigate or exacerbate market sensitivity. These clustering results thus form the foundation for understanding the role of board structure in shaping stock volatility.

Using the Elbow Method and the Dendrogram ensured that the chosen number of clusters was statistically sound and interpretable. By applying these two techniques in conjunction, the study provides a solid basis for the segmentation of companies, ensuring that the subsequent analysis is built on a robust clustering framework.

3.4. Train-Test Split and Model Selection

Once the companies were clustered, the dataset was split into training and test sets using a 70/30 ratio. The training set (70% of the data) was used to build and tune the machine-learning models, while the test set (30%) was reserved for evaluating the performance of the models. The dependent variable was the assigned Beta cluster, and the independent variables were the governance and financial metrics described above.

3.5. Machine Learning Models

The choice of machine learning models in this study is rooted in both theoretical justification and empirical findings from relevant literature, which underscore the models' ability to capture the complex relationships between board structure and market sensitivity (Beta). The selected models—Logistic Regression, Decision Tree, Naive Bayes, Ridge Classifier, and Bagging Classifier—each offer unique strengths that make them well-suited for the task at hand.

Logistic Regression has long been a cornerstone in the field of classification, particularly within financial applications. Its ability to estimate probabilities and provide interpretable coefficients makes it an effective tool for credit risk modeling, as noted by (Montevechi et al., 2024). However, while logistic regression is effective, it is typically outperformed by models like k-Nearest Neighbors (kNN) in terms of accuracy (Malhotra et al., 2024).

Decision Trees are another important tool, often selected for their capability to handle both numerical and categorical data, a trait particularly useful in modeling the interactions between governance characteristics and Beta. However, decision trees tend to be outperformed by more advanced ensemble methods like bagging and boosting, as highlighted by (Tsai et al., 2016).

Naive Bayes, known for its efficiency in high-dimensional settings, assumes feature independence, which is often a simplifying assumption in complex financial datasets. Kandula et al., (2024) emphasize that while Naive Bayes is well-suited for simple tasks, it is typically outperformed by more intricate models like decision trees and random forests. Its inclusion in this study ensures a balance of simplicity and computational efficiency.

Ridge Classifier, incorporating L2 regularization, proves advantageous in scenarios involving multicollinearity, a common occurrence in high-dimensional financial data. As Amin et al., (2022) and Aldahmani and Zoubeidi, (2020) assert, ridge regression's ability to manage overfitting is particularly valuable in financial contexts. It has been shown to outperform more complex models like Support Vector Machines (SVM) and neural networks in certain financial applications (Miura et al., 2019; Tran et al., 2023).

Finally, the Bagging Classifier offers the ability to reduce variance and prevent overfitting by aggregating multiple models, leading to enhanced accuracy and stability in predictions. Tsai et al., (2016) and Raju et al., (2023) found that bagging classifiers often outperform single models, including decision trees and logistic regression, which justifies its use in this study for capturing the non-linear dynamics between governance characteristics and market sensitivity.

The literature demonstrates that machine learning techniques, when applied correctly, can offer superior predictive power compared to traditional models in assessing financial risks. Alessi and Savona, (2021) emphasize the importance of advanced machine learning models for understanding complex, nonlinear, and multidimensional financial data. Similarly, Hermadi et al., (2020) note the significant role machine learning plays in predicting financial outcomes and improving risk management in the industry.

Table 2 summarizes the key strengths and comparative performance of each model based on existing studies, illustrating why these models were chosen for the analysis of Beta cluster predictions:

Table 2

Models Used in the Analysis

Model	Strengths	Performance
Logistic Regression	Effective for credit risk modeling in finance (Montevechi et al., 2024).	Outperformed by kNN in accuracy (Malhotra et al., 2024).
Decision Tree	Handles both numerical and categorical data (Montevechi et al., 2024).	Outperformed by ensemble methods like bagging and boosting (Tsai et al., 2016).
Naive Bayes	Efficient for high-dimensional data and simple tasks (Kandula et al., 2024).	Outperformed by complex models like decision trees and random forests (Kandula et al., 2024).
Ridge Classifier	Effective with multicollinearity in financial datasets (Amin et al., 2022; Aldahmani and Zoubeidi, 2020).	Outperforms SVM and neural networks in specific financial contexts (Miura et al., 2019; Tran et al., 2023).
Bagging Classifier	Reduces variance and overfitting by combining models (Tsai et al., 2016; Raju et al., 2023).	Outperforms single models like decision trees and logistic regression (Tsai et al., 2016; Raju et al., 2023).

3.6. Model Evaluation

The models were evaluated using accuracy, precision, recall, and F1-score metrics to assess their performance in predicting the Beta cluster for each company. These metrics provide a comprehensive view of each model's effectiveness, capturing the correct classifications (accuracy) and the balance between precision and recall. The evaluation results are presented in a comparative table, highlighting each model's strengths and weaknesses in predicting market sensitivity.

3.7. Machine Learning Model Performance

Several machine learning models were employed to predict a company's assigned Beta cluster based on its governance and financial characteristics. The models—Logistic Regression, Decision Tree, Naive Bayes, Ridge Classifier, and Bagging Classifier—were trained on 70% of the data, with the remaining 30% used for testing and evaluating their predictive performance. Each model's performance was assessed based on accuracy, precision, recall, and the F1-score, which collectively provided a comprehensive view of how well the models predicted the market sensitivity clusters.

Table 3 below presents the results for the five machine learning models:

Table 3
Accuracy Metrics of Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.63636	0.42727	0.63636	0.50505
Decision Tree	0.90909	0.92727	0.90909	0.90765
Naive Bayes	0.90909	0.92727	0.90909	0.90765
Ridge Classifier	0.63636	0.41234	0.63636	0.49823
Bagging Classifier	0.90909	0.92727	0.90909	0.90765

The results indicate that the Decision Tree, Naive Bayes, and Bagging Classifier models outperformed the Logistic Regression and Ridge Classifier models, achieving an accuracy of 90.9%. These models also achieved higher precision, recall, and F1 scores, suggesting that they could classify companies accurately into their respective Beta clusters. The Bagging Classifier demonstrated predictive solid performance on the test set, possibly due to its ability to capture non-linear relationships between governance variables and Beta. However, this performance should be further evaluated to ensure that it is not a result of overfitting.

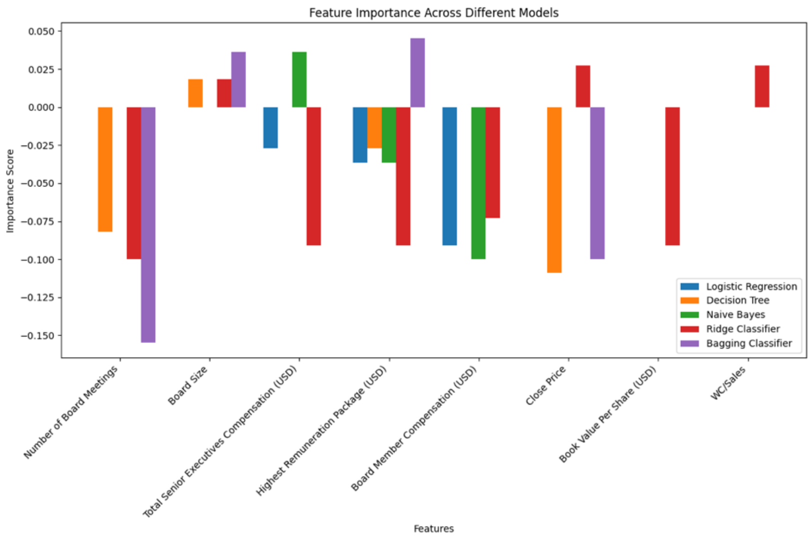
On the other hand, Logistic Regression and Ridge Classifier exhibited lower accuracy (63.6%) and performed less well across precision and recall metrics. Given the likely non-linear relationships inherent in the data, these linear models needed help to capture the complex interactions between governance variables and Beta.

3.8. Feature Importance Results

To further explore the contribution of each governance variable to the prediction of Beta clusters, Permutation Feature Importance was applied across the five machine learning models. This method provided insight into which features impacted the models' predictions most by measuring how much accuracy decreased when a feature was randomly shuffled. The table below summarizes the importance of each feature:

Figure 6

Feature Importance of Models



The feature importance analysis highlights critical governance and financial factors influencing Beta across five machine learning models. As shown in Figure 6, among the most significant features, the number of board meetings had a strong negative impact on the Decision Tree (-0.08182), Ridge Classifier (-0.10000), and Bagging Classifier (-0.15455). This suggests that more frequent meetings are associated with reduced Beta and better risk management. The highest remuneration package also showed notable influence in the Bagging Classifier (0.04546), indicating a correlation between higher executive pay and greater market sensitivity. However, other models, such as the Decision Tree and Ridge Classifier, reported weaker negative relationships. Close price exhibited mixed effects, significant in the Decision Tree (-0.10909) and Ridge Classifier (0.02727), reflecting its varying influence on Beta depending on the model.

Board size showed moderate importance, positively impacting the Decision Tree (0.01818) and Bagging Classifier (0.03636), suggesting that larger boards may help reduce volatility. Total senior executives' compensation played a varied role, with positive importance in Naive Bayes (0.03636) but adverse effects in Logistic Regression (-0.02727) and Ridge Classifier (-0.09091), revealing mixed outcomes about market sensitivity.

Other features, such as WACC Equity Risk Premium (%) and female representation on the board, had no significant influence across all models. Similarly, the corporate governance board committee, book value per share, WC/Sales, and board member compensation showed minimal or no impact, indicating limited relevance to Beta prediction.

4. Discussion

The findings of this study suggest that board structure plays a significant role in influencing a company's market sensitivity, as measured by Beta, in the software industry. This is consistent with Koerniadi et al., (2014) who found that larger boards tend to reduce risk-taking behavior, thereby contributing to lower Beta values. In the context of software firms, where innovation and rapid market shifts are common, increased board oversight may provide a stabilizing influence, helping to mitigate market fluctuations. This aligns with previous research suggesting that larger boards offer broader expertise, which can enhance governance capabilities and reduce systematic risk (Wang and Hsu, 2013; Yermack, 1996)

Frequent board meetings were also found to lower stock price volatility, reflecting better risk management practices. This supports the work of Sherif et al., (2024), who showed that companies with more frequent governance activities are better equipped to handle market volatility. The increased frequency of board meetings allows for more timely interventions and adjustments to strategic decisions, which can reduce a firm's sensitivity to external market changes. This finding is particularly relevant for software firms, where rapid technological advancements require agile decision-making. The importance of frequent governance interventions has also been highlighted in earlier studies focusing on high-growth industries (Elumaro and Ibrahim, 2023; Pearce and Patel, 2018).

In contrast to Chaudhary, (2021), who found that board independence increased volatility in emerging markets, this study did not observe a strong relationship between board independence and Beta in the software sector. This discrepancy could be attributed to the unique nature of the software industry, which demands greater strategic flexibility and innovation. In such sectors, independent directors may have a more limited role in managing volatility compared to industries where risk mitigation is driven by external oversight. Li et al., (2024) also noted that the effectiveness of board independence may vary significantly across different industries, further suggesting that industry-specific factors could moderate the relationship between governance mechanisms and firm risk.

The relationship between executive compensation and market sensitivity, as observed in this study, aligns with Koerniadi et al., (2014) who suggested that higher executive compensation is often associated with greater risk-taking behaviors. This connection between compensation and Beta suggests that compensation structures in software firms may incentivize strategies that heighten exposure to market volatility. Previous research by Mishra and Kapil, (2018) supports this, showing that executive compensation linked to firm performance can drive decisions that increase risk. The role of executive compensation in shaping a firm's risk profile warrants further investigation, particularly in sectors where rapid growth and technological innovation are critical.

Additionally, this study extends the work of Arisoy et al., (2015) by applying machine learning models to capture the non-linear relationships between governance variables and Beta. The use of clustering techniques to analyze software firms emphasizes the sector-specific nature of volatility, as suggested by (Maheshwari and Naik, 2024). Machine learning allows for more nuanced insights into how different governance mechanisms interact with market factors, revealing patterns that traditional linear models might overlook. This approach is consistent with recent advances in financial modeling, where complex algorithms are increasingly employed to predict market behavior and risk sensitivity (Lamba et al., 2024; Suleymanov et al., 2024).

The findings also resonate with broader research on corporate governance and its impact on firm risk. For example, Sharma et al., (2023) found that corporate governance mechanisms, such as ownership structure and board diversity, significantly influence a firm's risk profile in emerging markets. Although the software industry operates in a different context, these broader governance mechanisms still play a crucial role in shaping market sensitivity. The interplay between governance structures and risk is also highlighted in studies examining different industries, such as manufacturing and telecommunications Gerged et al., (2023) and Yuan et al., (2023), further illustrating the varied impact of governance practices across sectors.

5. Conclusion

This study aims to examine the relationship between board structure and stock market sensitivity, specifically focusing on how governance variables such as board size, meeting frequency, and executive compensation impact the prediction of Beta for software companies listed on the NASDAQ Global Select Market. By employing machine learning models, this research seeks to provide a deeper understanding of how these board characteristics influence a firm's Beta, which reflects the company's sensitivity to market fluctuations.

The results show that decision tree-based models, including the Decision Tree, Naive Bayes, and Bagging Classifier, outperformed logistic and ridge regression models in predicting a company’s Beta cluster. These models achieved an accuracy of 90.9%, along with high precision, recall, and F1 scores on the test dataset, suggesting that they identified patterns between governance factors and market sensitivity. However, further validation is necessary to confirm these findings. Conversely, Logistic Regression and Ridge Classifier models performed less well, likely due to their inability to handle the non-linear relationships in the data.

Feature importance analysis revealed that governance variables such as the Number of Board Meetings and Executive Compensation significantly impacted Beta prediction across several models. Specifically, more board meetings were associated with reduced Beta values, which may indicate that more frequent governance oversight is linked to more stable company performance. On the other hand, executive compensation, especially the Highest Remuneration Package, was associated with increased market sensitivity, implying that higher compensation may incentivize riskier behavior among executives. However, other governance variables like Females on Board and Board Committees showed limited influence across all models, indicating that their role in predicting Beta might be more nuanced in the context of the software industry.

These findings could have implications for investors and corporate leaders. When assessing software companies' risk profiles, investors might consider governance structures as one factor. Similarly, corporate leaders could explore optimizing governance practices, such as adjusting the frequency of board meetings or reviewing executive compensation structures, to influence market sensitivity and potentially support long-term stability.

Despite these contributions, this study has several limitations. The focus on software firms listed on NASDAQ limits the generalizability of the findings to other sectors. Moreover, some governance factors, such as board diversity, did not emerge as significant predictors in this context, suggesting that future research should explore these dynamics in greater depth, possibly using more extensive or diverse datasets.

Further research should consider additional governance variables or examine how these relationships evolve in other high-growth industries. Expanding the analysis beyond the software industry and employing more advanced machine learning techniques could provide even greater insight into how governance structures influence market sensitivity.

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