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Unveiling the Effects of Key Audit Matters on Stock Market Indicators: The Effectiveness of PCA and Curvilinear Regression

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Kilit Denetim Konularının Borsa Göstergeleri Üzerindeki Etkilerinin Ortaya Çıkarılması: PCA ve Eğrisel Regresyonun Etkinliği	**Unveiling the Effects of Key Audit Matters on Stock Market Indicators: The Effectiveness of PCA and Curvilinear Regression**

Öz

Bu çalışma, Borsa İstanbul'da işlem gören 95 şirketin kilit denetim konularının borsa performansı üzerindeki etkilerini incelemektedir. Maddi Duran Varlıklar, Maddi Olmayan Duran Varlıklar, Stoklar, Hasılat, Ticari Alacaklar, Ticari Borçlar ve Nakit gibi kilit denetim konuları, fiyat kazanç oranı, piyasa değeri/defter değeri oranı ve hisse başına kazanç ile ilişkilendirilmiştir. Kilit denetim konuları arasındaki yüksek korelasyon nedeniyle PCA ile boyut azaltımı yapılmıştır. Doğrusal ve eğrisel regresyon analizleri sonucunda, eğrisel modelin daha düşük MSE ve MAE değerleri ve anlamlı p-değerleri ile daha yüksek doğruluk ve uyum sağladığı tespit edilmiştir.

Abstract

This study examines the effects of key audit matters on the stock market performance of 95 companies traded on Borsa Istanbul. Key audit matters such as Tangible Fixed Assets, Intangible Fixed Assets, Inventories, Revenue, Trade Receivables, Trade Payables and Cash are associated with the price-earnings ratio, market value/book value ratio and earnings per share. Due to the high correlation between key audit matters, dimensionality reduction has been performed using PCA. As a result of linear and curvilinear regression analyses, it has been determined that the curvilinear model provided higher accuracy and fit with lower MSE and MAE values and significant p-values.

Anahtar Kelimeler: Kilit Denetim Konuları, Boyutsallık Azaltma, Regresyon Modelleri

Keywords: Key Audit Matters, Dimensionality Reduction, Regression Models

JEL Kodları: M40, M49

JEL Codes: M40, M49

Araştırma ve Yayın Etiği Beyanı	Bu çalışmada kullanılan veri seti, kamuya açık platformdan elde edildiğinden dolayı etik kurul izni gerekmemektedir.
Yazarların Makaleye Olan Katkıları	Çalışmanın tamamı yazar tarafından hazırlanmıştır.
Çıkar Beyanı	Yazarlar açısından ya da üçüncü taraflar açısından çalışmadan kaynaklı çıkar çatışması bulunmamaktadır.

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1. Introduction

Today, the dynamics in financial markets and decision-making processes related to business performance have become increasingly complex for both investors and businesses. The performance of companies traded on national stock exchanges such as Borsa Istanbul is affected by a number of factors. The most important of these factors are the financial status of companies and their auditing processes. In this context, the impact of auditing matters on business performance has become an important area of research. Auditing matters are related to the accuracy and reliability of an organization's financial statements and are therefore of critical importance to investors and other stakeholders.

Financial reports contain a significant amount of financial information that can assist decision-makers in their decision-making processes. The way managers present information can make significant contributions to understanding corporate decisions by revealing certain managerial characteristics or motivations (Li, 2011:2). The purpose of independent audit reports is to communicate key audit matters to investors and investment decision-makers and to improve investors' understanding of the auditor's role and responsibility in the audit. An important advantage recognized by supervisory authorities but often overlooked is the impact of KAMs (Key Audit Matters) on financial reporting (Gold, Heilmann, Pott and Rematzki, 2020:235). Disclosure of KAMs ensures that the judgments made by management and auditors during the preparation and audit of financial statements become more transparent. In this way, auditors have the opportunity to share their views on key matters related to companies with financial statement users (Lin and Yen, 2022:2).

The aim of the study is to assess the effects of the most frequently disclosed key audit matters on the stock market performance indicators of companies listed on Borsa Istanbul. In this context, the study evaluates the influence of key audit matters such as Tangible Fixed Assets (TFA), Intangible Assets (IA), Inventories (INV), Revenue (REV), Trade Receivables (TR), Trade Payables (TP), and Cash on stock market performance indicators, including price-earnings ratio (P/E), market-to-book value ratio (MBVR), and earnings per share (EPS). To analyze these effects, the study employs both linear and curvilinear regression models. Linear regression is applied to capture the direct, proportional relationships between variables, while curvilinear regression explores non-linear interactions. These regression models serve as tools to assess how key audit matters impact stock market performance indicators. In addition, the study utilizes Principal Component Analysis (PCA) to create new dimensions from the identified key audit matters, offering new perspectives in financial analysis and audit practices. Specifically, the study proposes the terms "Asset Evaluation Score" for PCA 1 and "Operational Impact Score" for PCA 2. These nomenclatures emphasize an asset and operational-oriented approach, moving beyond traditional financial auditing concepts. The proposed terms aim to contribute to the literature by enhancing the understanding of financial performance analysis in relation to key audit matters. For researchers and professionals in the fields of financial analysis and auditing, these newly defined dimensions can provide crucial insights. Understanding how key audit matters influence a company's financial performance offers investors and other stakeholders accurate, actionable information. Furthermore, audit processes, by ensuring the accuracy and reliability of financial statements, promote market transparency and bolster investor confidence. However, examining the effects of key audit matters demands a broader view, taking into account not only financial data but also long-term corporate performance and market value. Therefore, analyzing the detailed relationships between key audit matters and financial indicators can significantly enrich both academic literature and practical financial applications. Ultimately, this study aims to enhance the understanding of the complex interplay between financial data and auditing, providing valuable insights for developing financial analysis and investment strategies.

2. Literature Review

The purpose of disclosure of KAMs is to provide financial information to the parties using the financial statements. However, it is not possible to make a definitive judgment on whether the disclosures regarding KAMs are informative or not. While some studies on KAMs reveal that disclosures regarding these matters affect investors' decisions (Christensen, Glover and Wolfe, 2014), some studies state that the information disclosed in audit reports regarding KAM does not provide significant additional information (Gutierrez, Minutti-Meza, Tatum, and Vulcheva, 2018:1579; Liao, Minutti-Meza, Zhang and Zou, 2019:33-34). The study conducted by Velte and Issa (2019) presents a literature review of 49 empirical studies on KAMs disclosed in independent audit reports. The study examines the impact of KAMs disclosures on the reactions of shareholders, debtors, external auditors, boards of directors and other stakeholders in five main areas. The findings of the study indicate that KAMs disclosures generally have mixed effects on USA investor reactions and most studies do not show significant changes.

While there are no academic studies investigating the relationship between key audit matters and stock market performance indicators in Turkey, studies conducted abroad are also limited. Therefore, this study is expected to make a significant contribution to the literature. Examples of studies conducted abroad include the following. The study conducted by Altawalbeh and Alhajaya (2019) examines the impact of disclosure of KAMs by companies listed on the Jordanian stock exchange on investor reactions measured by abnormal trading volume. In the study, KAMs are considered as independent variables such as company size, return on assets, market value/book value ratio, leverage and market class. The manual content analysis conducted in the study reveals that the manufacturing sector ranks first in terms of KAMs disclosed in audit reports. According to the regression analysis results of the study, it is stated that KAMs, which are mandatory to be disclosed according to ISA701, have a significant impact on investor decisions. As a result, it is stated that the results obtained in the study support the idea that the disclosure of KAMs significantly affects investor behavior. Zhai, Lu, Shan, Liu and Zhao (2021) conducted a quasi-experimental study in China using a difference-in-differences approach, providing causal evidence that KAMs disclosures increase company-specific information and reduce the synchronicity of stock prices. According to the results, it is stated that this effect of KAMs disclosures becomes more pronounced, especially in companies with controlling shareholders and fewer institutional shareholders. The study also states that KAMs disclosures reduce the costs of obtaining information about the company's operating results, especially for outside shareholders, and facilitate the reflection of company-specific information in prices when access to outside shareholders is limited. In the study conducted by Gu and Ncuti (2020), the impact of key audit matters on market behavior is examined, the periods before (2014-2015) and after (2017-2018) the implementation of KAMs in China are compared and the cumulative abnormal returns of 52 A shares traded on the Shanghai and Shenzhen Stock Exchanges are analyzed. According to the Hausman test results conducted in the study, it is stated that the random effects model is appropriate for this study. As a result of the study, it is stated that the disclosure of KAMs does not have a significant impact on market behavior. In the study conducted by Ittarat and Tangpinyoputtikhun (2019), it is stated that the relationship between KAMs and stock returns and the factors that may affect KAMs have been determined by collecting the financial data of 256 companies traded on the Stock Exchange of Thailand between 2014 and 2017. It is stated that the hypotheses of the study have been tested with three different methods, namely Anova, market model and OLS regression analysis. As a result of the study, it is stated that KAMs generally do not have a significant effect on stock returns, but the type of audit firm, audit fee and ROE have a significant effect on KAMs. Liu, Yen, and Wu (2022) have investigated the relationship between user-perceived sentiments on KAMs and current and future firm performance. The study also investigates the validity of the BERT model to automatically extract KAMs sentiment analysis from audit reports of listed firms in Taiwan. Using manually labeled sentiment data in 2017 and BERT-extracted data in 2018, positive relationships have been found between KAMs sentiment and firm performances (Tobin Q, ROA, ROE). In particular, it has been found that the relationship between KAMs sentiment and firm market performance (Tobin Q) was stronger in 2018 than in 2017. These findings show that KAMs sentiment reflects future firm performance and that the BERT model is applicable in text mining. The study offers important implications for regulators, practitioners, and academics.

These studies examine the impact of KAMs on firm performance and investor behavior from different perspectives and present important findings in terms of the impact of KAMs on both market and firm performance.

3. Key Audit Matters

In recent years, the International Auditing and Assurance Standards Board (IAASB) has focused on improving the clarity of auditing standards and on audit reporting and audit quality. Through the "Clarity Project", which started in 2009, the IAASB reviewed all existing auditing standards to improve clarity and quality (IAASB, 2009). In 2011, the IAASB launched "Enhancing the Value of the Auditor's Report: Exploring Options for Change" in 2011 and issued an invitation for comments on "Improving the Auditor's Report" in 2012. The regulator's most recent work was in 2013, when it issued a consultation paper entitled "New and Revised International Standards on Auditing: Invitation for Comment" in 2013. The new draft includes a new standard, ISA 701: Communicating Key Audit Matters in the Independent Auditor's Report (IAASB, 2013). Paragraph 8 of the standard describes the purpose of communicating Key Audit Matters (KAMs) as "those matters that, in the auditor's professional judgment, are most significant to the audit of the financial statements". In Turkey, BDS 701 Standard on Disclosure of Key Audit Matters in the Independent Auditor's Report has been published in the Official Gazette dated 09/03/2017 and numbered 30002 to be applied for the audits of the accounting periods starting on and after 01/01/2017 for listed companies and 01/01/2018 for other companies subject to audit in accordance with the Turkish Commercial Code No. 6102 (www.kgk.gov.tr).

In a separate section of the report, the auditor describes each key audit matter using an appropriate subheading. The opening sentence in this section is as follows (ISA701):

(a) The key audit matters are those matters that, in the auditor's professional judgment, have of most significance in the audit of the financial statements [for the current period]; and

(b) These matters have been addressed in the context of the audit of the financial statements as a whole and in forming the auditor's opinion thereon, and the auditor does not provide a separate opinion on these matters

The increased transparency provided by KAMs helps reduce investors' uncertainty regarding auditing, increases investors' perception of trust in auditors, and ensures that their work is appreciated. It is predicted that the inclusion of KAMs in an audit report will increase investors' perceptions of auditor credibility (Moroney, Phang, and Xiao, 2021:68). The explanation of the KAM means explaining why the matters have been considered one of the most important matters during the audit and, in relation to this fact, why it has been identified as a key matter and how these matters have been addressed during the audit (Mamcarczyk, Popławski and Zieniuk, 2020:454).

4. Methodology

4.1. Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is widely used in the study of functional data, as it makes it possible to analyze a problem that is essentially infinite in size in finite dimensions (Hall and Hosseini-Nasab, 2006:109). PCA is based on the fact that at least some variables in the data set are correlated with each other. If none of the p variables are correlated with one another, there is already a set of uncorrelated axes and there is no point in doing principal component analysis. Correlation refers to the relationship between two variables - how much they vary together. The most commonly used measure is Pearson's product-moment correlation coefficient, which is a parametric measure and represents a linear relationship. It is defined as the covariance between two variables divided by the square root of the two variances (Daultrey, 1976:5). One might start with thirty original variables but want to create a set that might end up with only two or three meaningful axes. The formal name for the approach of rotating the data to show a decreasing variance on each successive axis is known as PCA or TCA. TBA creates the axes by generating linear combinations of the original variables, also known as principal components or PCs (Holland, 2008:1). Therefore, PCA is a powerful tool for managing large data sets. It is used to understand the relationships between the principal components and to explain the overall structure of the data while reducing the size of the data. This process allows for more complex analyses by revealing the underlying structure and patterns among the data. Especially when used to understand and summarize the effects of a large number of variables, PCA plays an important role in the structural analysis of data and modeling processes.

4.2. Linear and Curvilinear Regression Models

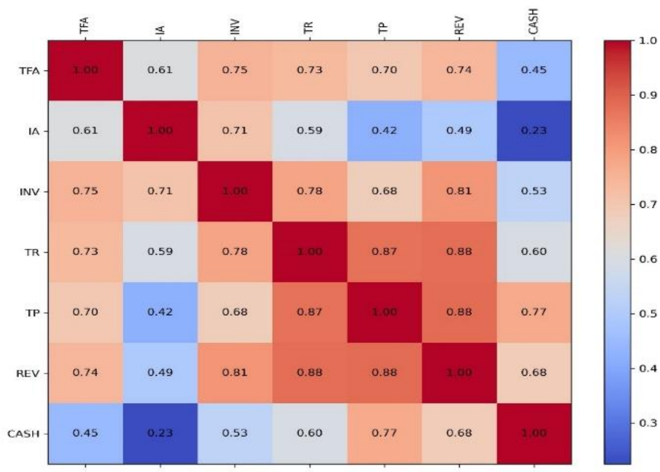
Regression problems begin with a set of potential variables. Some of these variables may be continuous variables, such as the height or weight of an object, while others may be ordinal but discrete. An example of this is a doctor rating a patient's general health on a nine-point scale. Some predictors may be categorical; such as eye colour. These different types of variables are useful in multiple linear regression models. Multiple linear regression provides a broader generalization of simple linear regression by providing a model that can contain more than one term, not just an intercept and slope (Weisberg, 2005:51). Linear correlation analysis is a way to measure relationships that exist between two or more variables as long as the functions are truly or approximately linear. More complex curvilinear relationships have long been known, and various methods have been developed to determine them. However, curvilinear regression analysis is used to consequently determine the curvilinear relationship of two or more independent variables with a dependent variable (Ezekiel, 1924:431-432)

In this study, the financial reports of 95 companies traded on the Borsa Istanbul (BIST) for the year 2022 are used. Financial reports have been obtained from www.kap.gov.tr. In addition, the KAMs used in the study have been selected from the accounting findings commonly encountered in 73 audit files, excluding whistleblowing and complaint reviews, in the examination report of the Public Oversight Accounting and Auditing Standards Authority for 2022. PCA, a dimension reduction technique, has been applied due to the high correlation between the independent variables consisting of KAMs in the dataset. PCA has been used to reveal the hidden relationships between the variables in the data set and made the data set more understandable by reducing the dimensions. The two components obtained as a result of PCA have been used as representative of the independent variables. The PCA components (PCA1 and PCA2) are associated with the dependent variables of P/E, MBVR and EPS. In the study, a linear regression model has been applied to examine the linear relationship between the variables and a curvilinear regression model has been applied to model the relationship in a more complex way. Python programming language has been used for analysis and modeling. Python's data science libraries Pandas, NumPy and Scikit-learn have been used in the data set processing and model building processes.

6. Analysis and Findings

According to the correlation coefficients in Figure 1, there are significant correlations between revenue and TFA (0.74), TR (0.88) and TP (0.88); and between TFA and INV (0.75), TR (0.73), TP (0.70) and REV (0.74). Correlation coefficients have been calculated only between independent variables because it has been aimed to provide a better understanding of the relationships between independent variables and potential multicollinearity problems. Not including dependent variables makes the relationships of these variables with the independent variables clearer and simplifies the analysis of the model.

Figure 1: Correlation Table



High correlation among independent variables can complicate the analysis process and increase unnecessary duplication. Therefore, in this study, variables with a high correlation between KAMs that are common in accounting data and important in financial analysis are subjected to dimensionality reduction using PCA. PCA allows the relationship between variables to be expressed in fewer components while preserving the information represented by the original variables. In this way, complex data sets can be represented in fewer dimensions and in a more meaningful way, and the analysis process can become more understandable.

6.1. PCA Analysis

How many components to divide your data set into depends on the structure of the data and the purpose of the analysis. Usually, the purpose of PCA is to transform the dataset into a simpler form by reducing the variability in the dataset. Therefore, some factors need to be considered when determining the number of components for PCA. PCA selects the components in a way that preserves a large portion of the variance. Thus, it may make sense to select components that represent a large proportion of the total variability in the data set. Usually, variance explanation ratios are examined before PCA and a threshold is set, usually 80% or 90%.

Table 1: Variance Explanation Ratios of Components

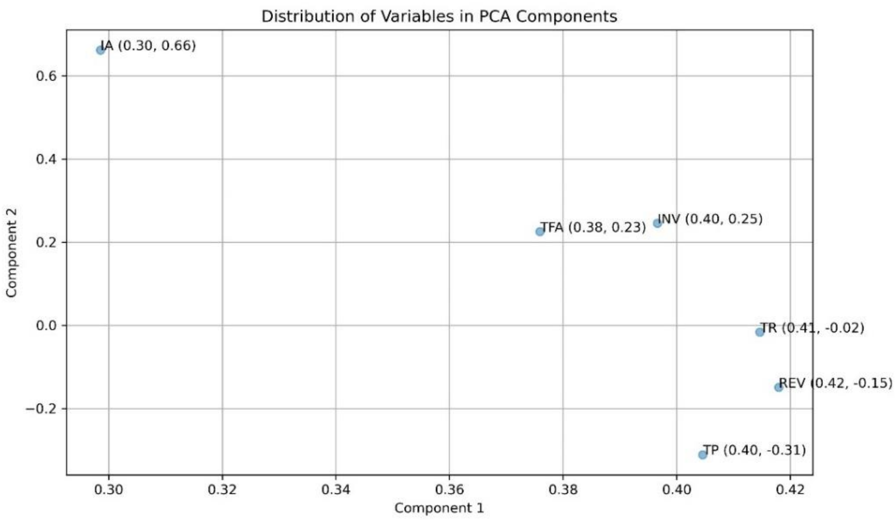
Components	Variance Explanation Ratios
Component 1	0.7201
Component 2	0.1356
Component 3	0.0520
Component 4	0.0385
Component 5	0.0315
Component 6	0.0127
Component 7	0.0097

It is important to determine how many components should be used by considering the variance explanation ratios of the components. The variance explanation ratios of the components show how much of the total variance each component explains. When Table 1 is examined, Component 1 explains approximately 72% of the total variance, Component 2 explains approximately 13% of the total variance and Component 3 explains approximately 5% of the total variance. Because these two components explain a large portion of the total variance. Although the third component also provides additional information, since it explains a smaller proportion of the total variance, it may be controversial to use the third component depending on the purpose of the analysis and the complexity of the model.

The components obtained by PCA are designed to be uncorrelated to ensure independence between them. Therefore, there is no linear relationship between PCA1 and PCA2; both components represent different variations in the dataset and do not affect each other. This is one of the basic principles of PCA, which indicates that each component provides separate information about the dataset during the dimensionality reduction process. That is, there is no trend with the value of PCA2 as the value of PCA1 increases, or conversely, there is no trend with the change in PCA1 as PCA2 increases. This indicates that PCA1 and PCA2 are independent components and represent different variations in the data set. This provides further insight into the variability and relationships in the dataset and informs about the effectiveness of the dimensionality reduction process.

The correlation of the Cash variable with other independent variables should also be taken into account in the construction of PCA components. If the Cash variable is not sufficiently correlated with other variables, it is not expected to carry a significant weight in the PCA components. In this study, it has been determined that the PCA results did not take into account the Cash variable. The distribution of the other independent variables on the PCA components is shown in Figure 2. Each point in Figure 2 represents the position of the relevant variable on the PCA components. This analysis helps to identify which variables are close to each other and which are different from each other. TFA and IA show a clear orientation towards component 1, while Inventories, TR, TP and REV are also oriented towards the PCA components, but with a weaker weight. In particular, the strong weight of TFA and IA in component 1 emphasizes the importance of these assets in the analysis. The distribution of PCA components can be used to identify relationships and differences between variables, thus making the analysis process more understandable. The distribution of PCA components can be used to identify relationships and differences between variables, making the analysis process more understandable. Analysing assets with this method can provide decision-makers with a more comprehensive financial view. Through regression equations, the effects of these components on financial performance can be examined.

Figure 2: Distribution of independent variables in PCA components



The Component Matrix results show the effects of the two main components obtained with PCA on the variables. Among the variables with the highest weights for Component 1, Trade Receivables (TR) and Revenue (REV) are noteworthy with values of 0.41 and 0.42, respectively. This situation shows that the effect of these variables on the first component is significant. In addition, Tangible Fixed Assets (TFA) and Inventories (INV) also make significant contributions with values of 0.38 and 0.40, respectively. Component 2 stands out with the highest weight of

0.66 for Intangible Assets (IA), which reveals that this variable is a determining element of the second component. In addition, Trade Payables (TP) and Revenue (REV) have negative weights, showing their negative effects on the second component with values of -0.31 and -0.15, respectively. These results provide an important framework for understanding the effects of the relevant variables on the main components. and develops new perspectives in financial analysis and auditing processes. In particular, the study proposes the terms "Asset Assessment Score" for Component 1 and "Operational Impact Score" for Component 2.

6.2. Linear Regression Equation

The linear regression equation has been determined as follows for each dependent variable.

$$P/E\ (Y) = -1.52 \times PCA1 - 54.69 \times PCA2 + 10.09$$

$$MBVR\ (Y) = 13.32 \times PCA1 - 0.96 \times PCA2 + 5.54$$

$$EPS\ (Y) = -3.02 \times PCA1 - 0.06 \times PCA2 + 3.37$$

When the PCA component coefficients of the P/E variable are examined, it is seen that PCA1 (-1.52) has a negative effect, while PCA2 (-54.69) has a greater effect. This shows that the effect of PCA2 on P/E is more pronounced than PCA1. In addition, the intercept (10.09) expresses the expected P/E value when the values of the PCA components are zero. This analysis helps to understand the effect of the P/E variable on the PCA components. When the PCA component coefficients of the MBVR variable are examined, it is seen that PCA1 (13.32) is positive and PCA2 (-0.96) is negative. This shows that the effect of PCA1 on MBVR is positive, that is, as PCA1 increases, MBVR also increases; however, the effect of PCA2 on MBVR is negative, that is, as PCA2 increases, MBVR decreases. The intercept (5.54) shows the expected MBVR value when the values of the PCA components are zero. This analysis helps to understand the effect of the MBVR variable on the PCA components. When the PCA analysis is performed for the EPS variable, it is found that PCA1 (-3.02) is negative and PCA2 (-0.06) is also negative. This shows that the effect of PCA1 on EPS is negative, that is, EPS decreases as PCA1 increases. However, considering that the PCA2 coefficient is quite low compared to the others, it can be stated that the effect of PCA2 on EPS is limited. The intercept (3.37) represents the expected EPS value when the values of the PCA components are zero.

This analysis provides useful information to explain the effect of the EPS variable on the PCA components. Linear regression shows the effects of the PCA components on each dependent variable and the relative importance between the PCA components. In particular, it reveals that the effect of PCA2 on the P/E variable is significantly greater than the other components and that this variable has a significant explanatory power. This situation emphasizes that PCA analysis is an important tool in understanding the relationships between the dependent variables and evaluating the explanatory power of the variables. The effects of PCA components on financial performance can be examined in more detail with curvilinear regression equations.

6.3. Curvilinear Regression Equation

The linear regression equation has been determined as follows for each dependent variable.

$$P/E\ (Y) = 1.24 \times PCA1 - 55.34 \times PCA1^2 - 0.62 \times PCA2 + 1.56 \times PCA2^2 - 0.07$$

$$MBVR\ (Y) = 3.93 \times PCA1 + 1.25 \times PCA1^2 + 2.13 \times PCA2 - 5.31 \times PCA2^2 + 0.23$$

$$EPS\ (Y) = -5.25 \times PCA1 + 0.46 \times PCA1^2 + 0.51 \times PCA2 - 1.26 \times PCA2^2 + 0.05$$

When the curvilinear regression equation of the P/E variable is examined, it is understood that explanations based on coefficient sizes should be made carefully. Direct use of coefficient sizes in second-degree polynomial equations can be misleading because coefficients can be affected by the scales of the variables. Therefore, large or small coefficients alone may not fully reflect the effect of the variable. For example, although the directly proportional coefficient of PCA1 (1.24) and the inversely proportional coefficient of $PCA1^2$ (-55.34) seem to have significant effects on the P/E variable, the main point to be considered is how these coefficients shape the relationship between the variables. Similarly, the positive ($PCA2^2$ = 1.56) and negative (PCA2 = -0.62) coefficients in the PCA2 component indicate a two-way interaction between the P/E variable and this component. This interaction indicates that PCA2 initially decreases P/E and then increases it from a certain point onwards.

When the curvilinear regression equation of the MBVR variable is examined, it is seen that the effect of the PCA components is significant. For example, the directly proportional coefficient of PCA1 (3.93) and the directly proportional coefficient of $PCA1^2$ (1.25) show that there is a positive and curvilinear relationship between MBVR and the PCA1 component. However, rather than the absolute magnitude of the coefficients, their signs and the curvilinear structure of the equation are more significant. In this case, it is understood that the effect of PCA1 on MBVR has a continuous increasing trend. Similarly, the directly proportional coefficient for the PCA2 component (PCA2 = 2.13) and the inversely proportional quadratic coefficient ($PCA2^2$ = -5.31) show that the MBVR variable first increases with the PCA2 component and then starts to decrease after a certain point. In terms of signs, positive first-order coefficients (PCA1 and PCA2) indicate that MBVR moves in the same direction as these components, while negative second-order coefficients ($PCA2^2$) indicate that the curve takes an inverted U-shaped structure and decreases at a certain point.

When the curvilinear regression equation of the EPS variable is examined, it is seen that the effect of the PCA components is again clearly revealed. For example, while the inversely proportional coefficient of PCA1 (-5.25) negatively affects the relationship between EPS and PCA1, the directly proportional coefficient of $PCA1^2$ (0.46) shows that this relationship has a curvilinear structure. This situation indicates that the PCA1 component initially causes a decrease in EPS, but after a certain point, it recovers in a curvilinear manner. In the PCA2 component, the directly proportional coefficient (PCA2 = 0.51) shows that EPS has a positive relationship with PCA2, while the negative quadratic coefficient ($PCA2^2$ = -1.26) indicates that this relationship reverses after a certain point and the decrease begins. When the signs are examined, an inverted U-shaped relationship is observed in PCA1, while in PCA2 there is a structure in which there is first an increase and then a decrease. In such curvilinear models, the signs and degrees of the coefficients provide a deeper understanding of the responses of EPS to the PCA components. This allows, in particular, to analyze the dynamics of financial performance more clearly. The cut-off point (0.05) also determines the starting level of the model, emphasizing the starting point of the curvilinear relationships.

The signs of the coefficients play a critical role in understanding how the variables interact. A positive coefficient indicates that the dependent variable increases with the increase in the independent variable, while a negative coefficient indicates an inverse relationship. Quadratic terms (for example, $PCA1^2$ and $PCA2^2$) express more complex curvilinear relationships, and whether these terms are positive or negative determines the direction of the curve. Positive quadratic coefficients shape the relationship between the variables in a U-shaped structure (increasing after a minimum point), while negative coefficients shape the relationship between the variables in an inverted U-shaped structure (decreasing after a maximum point). Such curvilinear models allow for the understanding of more detailed behaviors between the variables, going beyond linear relationships. In this context, the signs of both the first and second-order terms help to better understand the response of the P/E variable to different PCA components.

Figure 3 shows the relationship between the PCA1 component and the variables P/E, MBVR and EPS. The dots in blue represent how the PCA1 component is distributed with each dependent variable. The dots in red (P/E), orange (MBVR) and yellow (EPS) represent the forecasts made from the PCA1 component. For the P/E variable, the blue dots do not show a clear linear relationship with the PCA1 component, while the red forecasts show a more regular distribution. However, some blue dots are far from the red forecasts, which may increase the forecast errors. Similarly, the situation is similar for MBVR and EPS variables. The blue dots do not show a clear linear relationship with the PCA1 component, while the orange (MBVR) and yellow (EPS) forecasts exhibit a trend with respect to PCA1. However, some blue points are quite far from the orange and yellow predictions and the prediction errors in these points are high. These observations emphasize how effective the PCA1 component is in explaining the distribution of variables such as P/E, MBVR and EPS and how important it is in assessing the accurate prediction ability of PCA components.

Figure 3: Curvilinear regression analysis for PCA1

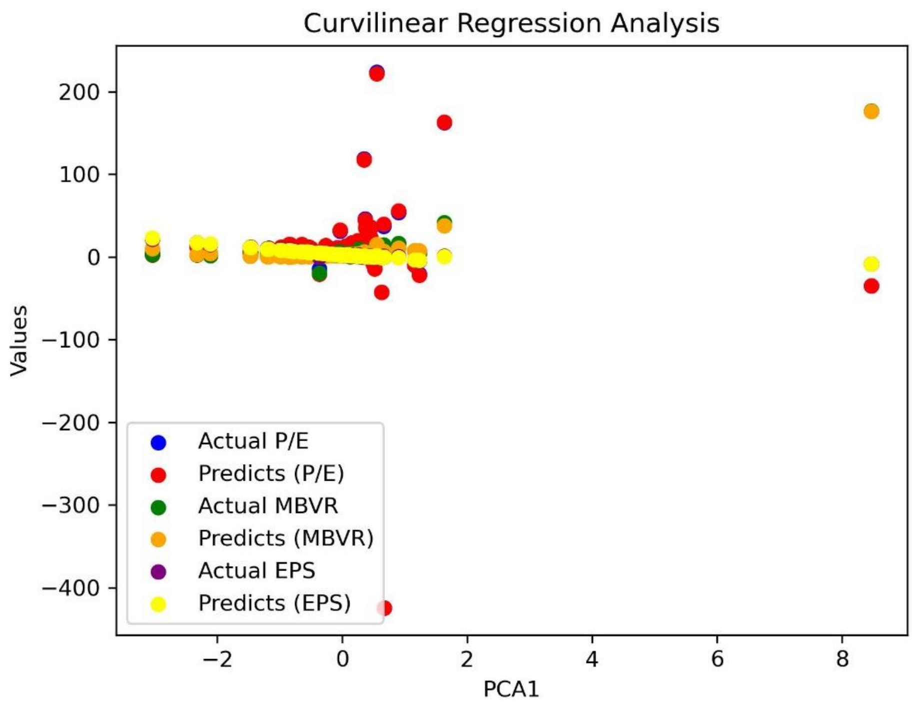
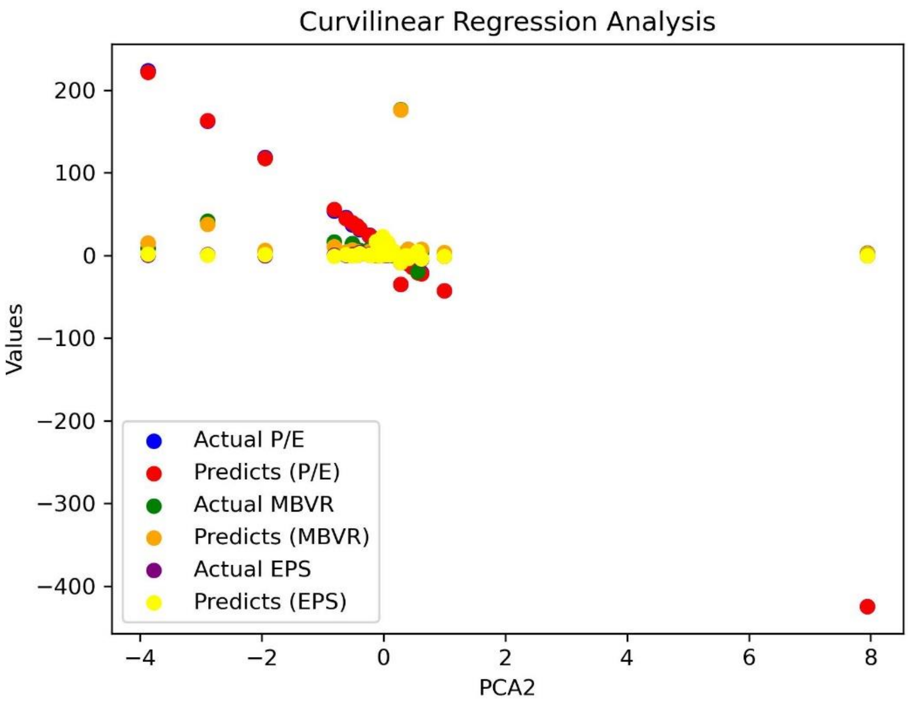


Figure 4 shows the estimates of the P/E, MBVR and EPS variables. First of all, for the P/E variable, the distribution of the blue dots does not show a clear linear trend with respect to the PCA2 variable, while the red estimates seem to be more uniformly distributed. However, it is observed that some of the blue dots are quite far from the red estimates, which may increase the estimation error. Similarly, for the MBVR and EPS variables, the distribution of blue dots does not show a clear trend with respect to PCA2, whereas the orange (MBVR) and yellow (EPS) estimates show a trend with respect to PCA2. However, it is observed that some blue points are quite far from the orange and yellow estimates and the estimation error is high in these points. These observations help to understand the ability of PCA components to predict accurately and how certain variables are distributed across PCA components.

Figure 4: Curvilinear regression analysis for PCA2



6.4. Performance of Regression Models

Table 2 shows the linear regression model performance results. The P/E model shows a very high performance. The R^2 value of the model is 0.9965, which shows that the model covers 99.65% of the variance explained by the independent variables. The adjusted R^2 is also quite high (0.9964), confirming that the model has a good performance despite its complexity. The F-statistic value is 13,128.82 and the p-value of this value is calculated as 0.0000; this shows that the model is generally significant and the independent variables are important in explaining P/E. When the coefficients are examined, it is observed that PCA1 has a negative effect (-1.4315) and PCA2 has a very large negative effect (-54.6028). The MBVR model has a lower performance. The R^2 value is 0.6427 and the adjusted R^2 is 0.6350. This shows that the independent variables explain 64.27% of the MBVR, but the explanatory power of the model is not very high. The F-statistic value is 82.75 and the p-value is 0.0000, which indicates that the model is statistically significant. The PCA1 coefficient is positive (13.0227) and has a significant effect on MBVR, while the PCA2 coefficient has a negative and lower effect (-1.2493). A similar situation is observed for the EPS model. The R^2 value is 0.6414 and the adjusted R^2 value is 0.6336. This indicates that the independent variables explain approximately 64.14% of the EPS. The F-statistic of the model is 82.28 and the p-value is again 0.0000, indicating that the model is generally significant. While the PCA1 coefficient (-3.0905) has a negative effect, the coefficient of PCA2 (-0.1344) shows a much smaller effect.

The P/E model has much higher explanatory power and accuracy compared to other models. The MBVR and EPS models are statistically significant, but their explanatory power is at a moderate level. In all three models, F-statistic values and p-values prove the significance of the model, but there are differences between the PCA1 and PCA2 coefficients in each model.

Table 2: Linear Regression Models Performance

Model	MSE	MAE	R^2	Adjusted R^2	F-statistic	Prob (Sig.)	PCA1 Coefficient	PCA2 Coefficient
P/E	10.4678	2.2246	0.9965	0.9964	13,128.8181	0.0000	-1.4315	-54.6028
MBVR	121.4858	7.5784	0.6427	0.6350	82.7526	0.0000	13.0227	-1.2493
EPS	6.8417	1.7985	0.6414	0.6336	82.2851	0.0000	-3.0905	-0.1344

When the results of the curvilinear regression model in Table 3 are examined, it shows a very successful performance for the dependent variables P/E, MBVR and EPS. The P/E model is the model with the highest performance. The R^2 value is 0.9997, indicating that the model explains 99.97% of the changes in P/E. The adjusted R^2 is also 0.9996, confirming that the model has a very strong explanatory power despite its complexity. The MSE (Mean Squared Error) is 1.0098 and the MAE (Mean Absolute Error) is 0.6289, indicating that the model's estimates are quite precise. The F-statistic value is 52,831.95, and the p-value is 0.0000. This shows that the model is statistically significant and strong. Looking at the coefficients, it has been observed that PCA1 had a positive effect with 1.2375, while PCA2 had a significantly negative effect with -55.3369. The MBVR model also performs quite well. The R^2 value is 0.9655, indicating that the model explains 96.55% of the variance in MBVR. The adjusted R^2 is 0.9632, indicating that the model has a very strong explanatory power. The MSE is 11.7190, and the MAE is 2.1424, indicating that the model has a low error rate. The F-statistic value is 498.68 and the p-value is 0.0000, indicating that the model is generally significant. While the PCA1 coefficient has a positive effect with 3.9299, the PCA2 coefficient is 1.2518, indicating that the effect on MBVR is lower but positive. The EPS model gives similar results to the MBVR model. The R^2 value is 0.9654, indicating that 96.54% of the variance in EPS is explained by the independent variables. The adjusted R^2 is calculated as 0.9631. The MSE is 0.6600 and the MAE is 0.5084, indicating that the model's estimates are quite accurate. The significance of the model is proven with the F-statistic value of 496.81 and the p-value of 0.0000. When the coefficients are examined, it is observed that PCA1 has a negative effect with -5.2483, while PCA2 has a positive but much smaller effect with 0.4591.

All three models have high explanatory power and statistical significance. While the P/E model is the best-performing model, the MBVR and EPS models also produce quite strong estimation results. The effects of PCA1 and PCA2 variables are different in each model, with the negative effect of PCA2 being very strong in the P/E model, while the effects of PCA1 and PCA2 appear to be more balanced in the EPS and MBVR models.

Table 3: Curvilinear Regression Models Performance

Model	MSE	MAE	R^2	Adjusted R^2	F-statistic	Prob (Sig.)	PCA1 Coefficient	PCA2 Coefficient
P/E	1.0098	0.6289	0.9997	0.9996	52,831.9471	0.0000	1.2375	-55.3369
MBVR	11.7190	2.1424	0.9655	0.9632	498.6811	0.0000	3.9299	1.2518
EPS	0.6600	0.5084	0.9654	0.9631	496.8057	0.0000	-5.2483	0.4591

When the curvilinear regression and linear regression models have been compared, the curvilinear regression model generally performed better. The R^2 value for P/E in the curvilinear model has 0.9997, and for MBVR and EPS it has 0.9655 and 0.9654, which provided higher explanatory power compared to the linear model. In addition, the F-statistic values have higher in the curvilinear model, and all three models provided significant results. In terms of coefficients, the effects of PCA1 and PCA2 in the curvilinear model have been more pronounced and different compared to the linear model. Especially in the P/E model, the negative effect of PCA2 has been observed stronger in the curvilinear model. This shows that the curvilinear model better captures the complex relationships in the data.

7. Conclusion

This study examines the relationship between KAMs and stock market performance indicators of 95 companies operating in Borsa Istanbul. The linear regression model results show that key audit matters such as Tangible Fixed Assets (TFA), Intangible Fixed Assets (IA), Inventories (INV), Revenue (REV), Trade Receivables (TR) and Trade Payables (TP) are related to stock market performance indicators such as P/E, MBVR and EPS. However, the linear model cannot adequately explain the complexity of these relationships. Curvilinear regression models reveal more complex and non-linear relationships between these issues and stock market performance indicators. While P/E has high explanatory power in both models, MBVR and EPS show higher performance in the curvilinear regression model compared to the linear regression model.

The findings obtained in the study clearly reveal the effects of the two main components (PCA1 and PCA2) on the dependent variables. In particular, both components have a negative effect on the P/E variable, but the effect of PCA2 is more pronounced. This situation shows that, in the case of the Turkish stock market, company assets and revenues reduce the P/E. For MBVR, PCA1 has a positive effect, while PCA2 has a negative effect; this situation indicates that while asset valuation increases MBVR, operational factors cause this ratio to decrease. Both components also have a negative effect on EPS, especially the effect of PCA1 is noteworthy. The findings indicate theoretically complex relationships and it can be stated that this situation may be specific to the Turkish stock market. In particular, the high valuation of assets creates a negative effect on profit and earnings per share; this may be due to imbalances in operational efficiencies in emerging markets. According to the analysis results, PCA2 has a stronger negative effect on the P/E. This situation reveals that the negative factors on the operational activities of the company reduce the P/E. On the other hand, while PCA1 provides a positive effect on the MBVR, the negative effect of PCA2 shows the effect of operational weaknesses as well as asset evaluation processes on this ratio. EPS, especially with the significant effect of PCA1, stands out as another important indicator that is negatively affected by the increase in asset values. These findings emphasize the importance of asset management and operational activities in the audit processes of companies on basic financial indicators such as P/E, MBVR and EPS. The Component Matrix results show that PCA1, which is associated with asset-based elements, focuses on the financial structure of the company and therefore creates a significant effect on P/E and EPS. PCA2, on the other hand, reflects the effects on MBVR and P/E from different aspects by being associated with secondary assets and commercial debts. These analyses reveal the necessity of companies to optimize their asset and operational performance.

The results of PCA analysis show that there are high correlations between KAMs such as TFA, IA, INV, REV, TR, TP and Cash and that these variables are related to stock market performance indicators. The use of PCA helped to identify complex relationships between variables and improve model performance. This study highlights the importance of using linear and curvilinear regression models to understand the impact of key audit matters on operating performance. It also shows that the use of dimensionality reduction methods, PCA, is a valuable tool for identifying relationships between variables and improving model performance. As a result, this study provides important guidance in the process of identifying and evaluating business performance. It also emphasizes the importance of using dimensionality reduction and regression models in financial analysis and makes a valuable contribution to the literature.

A limited number of studies have been conducted abroad to examine the impact of KAMs on investor behavior and market performance. For example, Altawalbeh and Alhajaya (2019) are found that KAMs disclosures have a significant impact on investors' decisions, while Zhai et al. (2021) found that KAMs disclosures facilitate the integration of firm-specific information into prices. However, Gu and Ncuti (2020) suggested that KAMs do not have a significant impact on market behavior. Liu et al. (2022) emphasized that KAMs sensitivity reflects firm performance and is a positive indicator of future market performance. In this context, the study is expected to make a significant contribution to the literature by examining the relationship between KAMs and stock performance in Turkey.

As a result, it is thought that this study will make a significant contribution to understanding the relationships between stock performance indicators of companies listed on Borsa Istanbul and KAMs. In this study, the use of linear regression and curvilinear regression models together reveals not only the linear but also the complex and non-linear aspects of these relationships. In particular, it is determined that the curvilinear regression model performed better than the linear regression model and explained the relationships more comprehensively. In addition, the use of PCA stands out as an effective tool in identifying high correlations and complex relationships between variables. These findings emphasize the importance of dimension reduction methods and regression models in understanding and analyzing the effects of KAMs on financial performance. In this field, where there are limited studies in the literature, this study examining the relationships between KAMs and stock performance in Turkey provides a valuable reference for better understanding investor behavior and market performance. Thus, it is anticipated that this study will be an effective guide for financial analyses and investment decisions.

These results are both consistent with theoretically known facts and reflect the dynamics specific to the Turkish stock market. The results observed in the Turkish stock market may differ, especially due to market conditions and economic fluctuations. In emerging markets such as Turkey, the effects of operational activities and asset management processes on profitability may have a more complex structure compared to developed markets. In this context, it is clear that the findings obtained require a more complex explanation in linear regression analysis. For example, interaction terms or polynomial terms can be added to increase the accuracy of regression models. Such additions can help us better understand the dynamic structure of the relationships between the components. In addition, the dynamics in different sectors in the Turkish stock market should also be taken into account; since sectoral differences can shape the effects of asset management and operational activities on financial indicators. Therefore, examining these analyses on a sectoral basis and considering the factors specific to Turkey's economic conditions will contribute to supporting the results with a more robust theoretical framework.

The results obtained provide important strategic information for stock market investors and speculators. Focusing on KAMs while making investment decisions can enable investors to make more conscious and profitable moves. In particular, elements such as asset valuation, operational efficiency and financial indicators are the main areas to be considered in investment decisions. First, the analysis made on the P/E shows the effect of the company's profitability on the market value. The strong negative effect of PCA2 on this ratio reveals that low operational efficiency and high asset values can negatively affect the stock price. In this case, investors should evaluate the P/E and consider the factors affecting the company's profitability and market value; they should prefer to focus on companies with high operational performance.

In terms of MBVR, the positive effect of PCA1 indicates that asset valuation can increase this ratio. Therefore, while companies with high asset values may be attractive to investors, the negative effect of PCA2 should also be taken into account. Investors can evaluate opportunities that will increase MBVR values and provide potential gains by focusing on companies that are strong in asset management. The analysis of the EPS variable provides an important criterion for investors to evaluate the profitability of the company. The negative effect of PCA1 indicates that high asset values can negatively affect earnings per share. In this context, investors' attention to EPS values and the company's asset management strategies will help them take the necessary steps to increase profitability.

As a result, stock market investors should analyze financial indicators such as P/E, MBVR and EPS to form their investment decisions based on these indicators and KAMs. This approach will help them make investments that are in line with market conditions and minimize potential risks.

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Extended Summary

Unveiling the Effects of Key Audit Matters on Stock Market Indicators: The Effectiveness of PCA and Curvilinear Regression

This study comprehensively examines the effects of the most frequently disclosed key audit matters in the independent audit reports of 95 companies traded on Borsa Istanbul on the stock market performance. The aim of the study is to determine the relationship between the most frequently disclosed key audit matters and the stock market performance indicators of the companies. The key audit matters are analyzed within the scope of the study are Tangible Fixed Assets (TFA), Intangible Fixed Assets (IA), Inventories (INV), Revenue (REV), Trade Receivables (TR), Trade Payables (TP) and Cash account items. These matters are associated with the stock market performance indicators, namely price earnings ratio (P/E), market value/book value ratio (MBVR) and earnings per share (EPS). The dataset is used in the study consists of financial reports of 95 companies traded on Borsa Istanbul as of 2022 and the reports have been obtained from www.kap.gov.tr. In addition, key audit matters have been selected from the accounting findings in 73 audit files, excluding whistleblower and complaint reviews, included in the 2022 audit reports of the Public Oversight, Accounting and Auditing Standards Authority.

In the first stage of the study, the Principal Component Analysis (PCA) model has been applied due to the high correlation between the independent variables in the data set. PCA reduces the dimensions of the variables in the data set and provides a more understandable representation of the data. According to the PCA results, the first two components (PCA1 and PCA2) represent a large portion of the variables in the data set. PCA1 explains approximately 72% of the total variance, while PCA2 explains 13%. The third component explains only 5% of the total variance, and therefore the use of the third component may be controversial depending on the purpose of the analysis and the complexity of the model. When the correlation matrix of PCA components with independent variables is examined, the zero correlation between PCA1 and PCA2 indicates that these two components are independent of each other and represent different variations in the data set. This situation provides an important contribution to understanding the relationships between variables in the data set of PCA components. In particular, it is observed that TFA and IA are proportionally oriented towards PCA1 component, while Inventories, TR, TP and REV are proportionally oriented towards PCA components. This emphasizes that TFA and IA play an important role in the analysis.

In this study, linear and curvilinear regression models have been applied. While linear regression is used to model linear relationships between variables, curvilinear regression models non-linear relationships between variables. Linear regression equations clearly show the linear effects of PCA components on P/E, MBVR and EPS. These equations are the basic models used to understand the relationship of each variable with PCA components.

P/E (Y) = $-1.52 \times PCA1 - 54.69 \times PCA2 + 10.09$

MBVR (Y) = $13.32 \times PCA1 - 0.96 \times PCA2 + 5.54$

EPS (Y) = $-3.02 \times PCA1 - 0.06 \times PCA2 + 3.37$

Curvilinear regression equations are used to model more complex relationships that include the effects of the squares of the PCA components.

P/E (Y) = $1.24 \times PCA1 - 55.34 \times PCA1^2 - 0.62 \times PCA2 + 1.56 \times PCA2^2 - 0.07$

MBVR (Y)= $3.93 \times PCA1 + 1.25 \times PCA1^2 + 2.13 \times PCA2 - 5.31 \times PCA2^2 + 0.23$

EPS (Y) = $-5.25 \times PCA1 + 0.46 \times PCA1^2 + 0.51 \times PCA2 - 1.26 \times PCA2^2 + 0.05$

These equations comprehensively examine the linear and nonlinear effects of PCA components on P/E, MBVR and EPS.

According to the performance results of the linear regression model, the P/E model exhibits a high performance. The R^2 value of the model is 99.65% and the adjusted R^2 value is 0.9964; this shows that the model is explained to a very large extent by the independent variables. The F-statistic is calculated as 13,128.82 and the p-value is 0.0000, proving that the model is statistically significant. The PCA1 (-1.4315) and PCA2 (-54.6028) coefficients show negative effects. In the MBVR model, the R^2 value is 0.6427 and the adjusted R^2 value is 0.6350. This shows that the model has a moderate explanatory power. The F-statistic is 82.75 and the p-value is 0.0000. PCA1 has positive (13.0227) effects and PCA2 has negative (-1.2493) effects. The EPS model also provides similar results. R^2 value is 0.6414, adjusted R^2 value is 0.6336. The significance of the model is confirmed by F-statistic (82.28) and p-value (0.0000). PCA1 (-3.0905) shows a negative effect, and PCA2 (-0.1344) shows a very low effect.

According to the performance results of the curvilinear regression model, P/E, MBVR and EPS models show high performance. The P/E model is the most successful model; the R^2 value is 0.9997, adjusted R^2 value is 0.9996. The MSE value is 1.0098, the MAE value is 0.6289, and the prediction accuracy of the model is high. The significance of the model is proven with F-statistics of 52,831.95 and the p-value is 0.0000. PCA1 shows a positive (1.2375) effect, PCA2 shows a negative (-55.3369) effect. MBVR model also has a strong performance. R^2 value is 0.9655, adjusted R^2 value is 0.9632. The MSE value is 11.7190, MAE value is 2.1424. The F-statistic is 498.68 and the p-value is 0.0000. PCA1 shows a positive effect (3.9299) and PCA2 shows a positive effect (1.2518). The EPS model produces similar results to MBVR. The R^2 value is 0.9654, the adjusted R^2 value is 0.9631. The MSE value is 0.6600, and the MAE value is 0.5084. The model is significant with the F-statistic of 496.81 and the p-value is 0.0000. PCA1 shows a negative effect (-5.2483) and PCA2 shows a positive effect (0.4591). As a result, all three models have high explanatory power and statistical significance. While the P/E model exhibits the best performance, the MBVR and EPS models also make strong predictions. The effects of PCA1 and PCA2 differ among the models.

The curvilinear regression model shows a stronger performance compared to the linear regression model. The P/E model explains almost all the variance with an R^2 value of 0.9997 and an adjusted R^2 value of 0.9996. In addition, the MBVR and EPS models also provide strong prediction results with an explanatory power of 96.55% and 96.54%, respectively. The MSE and MAE values are low, while the F-statistics and p-values prove the statistical significance of the models in general. These results show that the curvilinear regression model has a higher performance.