REPUBLIC OF TURKEY
ÇUKUROVA UNIVERSITY
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DEPARTMENT OF BUSINESS ADMINISTRATION

FUNDAMENTAL BETA WITH FIRM SPECIFIC VARIABLES AND ITS IMPLEMENTATION FOR DEVELOPED MARKETS

Toprak Ferdi KARAKUŞ

Ph.D. THESIS

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Ph.D. THESIS

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This study has been accepted as a DOCTORAL THESIS in the Department of Business Administration by our jury.

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Toprak Ferdi KARAKUŞ

İTHAF

To the cherished memories of my beloved mother Hikmet Karakuş and my esteemed professor Assoc. Prof. Dr. Gamze Vural.

ABSTRACT

FUNDAMENTAL BETA WITH FIRM SPECIFIC VARIABLES AND ITS IMPLEMENTATION FOR DEVELOPED MARKETS

Toprak Ferdi KARAKUŞ

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Supervisor: Prof. Dr. Hatice DOĞUKANLI
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Risk in financial markets is divided into two main categories: systematic (market-specific) and non-systematic (company-specific) risk. While systematic risk arises from general fluctuations in the market, the beta coefficient is used as a basic indicator in measuring this risk. However, firm specific variables and managerial dynamics can also significantly affect the sensitivity of the company to external environmental factors. Since the financial statements of companies reflect not only financial performance but also management style and internal dynamics, they allow a relationship to be established between systematic risk and firm specific variables.

The main purpose of the study is to analyze the effect of these factors that determine the financial performance of companies on systematic risk and to reveal the relationship between financial indicators and the beta coefficient. In other words, it is aimed to investigate whether firm-specific variables have an impact on the level of risks developing outside the firm The relationship between firm-specific variables and systematic risk was first introduced within the framework of the 'fundamental beta' concept in a study by Beaver, Kettler, and Scholes in 1970. In this study, the calculation of fundamental beta was conducted by incorporating a sample of 18 countries classified as developed by Morgan Stanley Capital International (MSCI), including Australia, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The annual financial data of a total of 418 companies operating in the energy, raw material and industry sectors between 2016 and 2023 were used within the scope of the sample. The dependent variable in the study is the beta coefficient, which is an indicator of systematic risk. The independent variables include dividend per share, quick ratio, return on assets, earnings before interest and taxes (EBIT), total assets, liabilties-to-assets ratio and asset turnover.

As a result of the study using the panel regression analysis method, it was found that asset turnover, dividend per share and return on assets have a negative and significant effect on the systematic risk coefficient, beta. A positive and significant effect of earnings before interest and taxes, liabilities-to-assets ratio and total assets on the systematic risk indicator beta coefficient was found.

In addition, cluster analysis method was used to test the existence of any effect specific to the countries in the sample used in the research. Accordingly, the companies in the sample were divided into 3 main clusters based on variables. In the regression results made by adding the clusters as dummy variables, it was revealed that the effect of the independent variables showing significant differences varied according to the companies in different clusters.

Keywords: Beta, risk, systematic risk, financial management, financial performance.

ÖZET

FİRMA İÇİ DEĞİŞKENLERİN SİSTEMATİK RİSKE ETKİSİ (TEMEL BETA) VE GELİŞMİŞ ÜLKE PİYASALARINDA UYGULANMASI

Toprak Ferdi KARAKUŞ

Doktora Tezi, İşletme Ana Bilim Dalı
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Finansal piyasalarda risk, sistematik (piyasaya özgü) ve sistematik olmayan (firmaya özgü) risk olarak iki ana kategoriye ayrılmaktadır. Sistematik risk, piyasada genel olarak yaşanan dalgalanmalardan kaynaklanırken, beta katsayısı bu riskin ölçülmesinde temel bir gösterge olarak kullanılmaktadır. Ancak, şirket içi değişkenler ve yönetimsel dinamikler de firmanın dış çevresel faktörlere olan hassasiyetini önemli ölçüde etkileyebilmektedir. Şirketlerin finansal tabloları, sadece mali performansı değil, aynı zamanda yönetim tarzını ve iç dinamikleri yansıttığı için sistematik risk ile finansal göstergeler arasında bir ilişki kurulmasına olanak sağlamaktadır.

Çalışmanın temel amacı, şirketlerin finansal performansını belirleyen bu faktörlerin sistematik risk üzerindeki etkisini analiz ederek, finansal göstergeler ile beta katsayısı arasındaki ilişkiyi ortaya koymaktır. Başka bir ifadeyle, firma içi değişkenlerin, firmanın dışında gelişen risklerin düzeyi üzerinde etkisinin olup olmadığı araştırılmak istenmektedir. Firma içi değişkenlerle sistematik risk arasındaki ilişki ilk olarak "temel beta" kavramı çerçevesinde Beaver, Kettler ve Scholes'in 1970 yılında yazdığı makalede ortaya konulmuştur. Bu çalışmada, temel beta hesaplaması, Morgan Stanley Capital International (MSCI) tarafından gelişmiş ülkeler kategorisinde yer alan 18 ülke (Avustralya, Kanada, Danimarka, Fransa, Almanya, Hong Kong, İrlanda, İtalya, Japonya, Hollanda, Yeni Zelanda, Norveç, Singapur, İspanya, İsveç, İsviçre, Birleşik Krallık ve Amerika Birleşik Devletleri) örnekleme dahil edilerek gerçekleştirilmiştir. Örneklem kapsamında, enerji, ham madde ve endüstri sektörlerinde faaliyet gösteren toplam 418 şirketin 2016-2023 yılları arasındaki yıllık finansal verileri kullanılmıştır. Çalışmada bağımlı değişken, sistematik risk göstergesi olan beta katsayısıdır. Bağımsız değişkenler arasında temettü oranı, asit-test oranı, aktif karlılık, faiz ve vergi öncesi kar (FVÖK), toplam varlıklar, toplam borcun varlıklara oranı ve varlık devir hızı yer almaktadır.

Panel regresyon analiz yönteminin kullanıldığı araştırmanın sonucunda, aktif devir hızı, hisse başına temettü ve aktif karlılığının sistematik risk katsayısı olan beta üzerinde negatif ve anlamlı bir etkiye sebep olduğu bulunmuştur. Faiz ve vergi öncesi karın, toplam borcun varlıklara oranının ve toplam varlıkların sistematik risk göstergesi beta katsayısı üzerinde pozitif ve anlamlı etkisi bulunmuştur.

Ayrıca, araştırmada kullanılan örneklemdeki ülkelere özgü herhangi bir etkinin varlığını test etmek amacıyla kümeleme analizi yöntemi kullanılmıştır. Buna göre örneklemde yer alan şirketler, değişkenler bazında 3 ana kümeye bölünmüştür. Kümelerin kukla değişken olarak eklenmesiyle yapılan regresyon sonuçlarında anlamlı farklılıklar gösteren bağımsız değişkenlerin etkisinin, farklı kümelerde yer alan şirketlere göre değiştiği ortaya çıkmıştır.

Anahtar Kelimeler: Beta, risk, sistematik risk, finansal yönetim, finansal performans.

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ABBREVIATIONS

AT	Asset Turnover
CAPM	Capital Asset Pricing Model
CCAPM	Consumption-Based Capital Asset Pricing Model
C-CAPM	Conditional Capital Asset Pricing Model
CMIE	Centre for Monitoring Indian Economy
CML	Capital Market Line
DPS	Dividend per Share
DW	Durbin-Watson
EBIT	Earnings Before Interest and Taxes
EMH	Efficient Market Hypothesis
ESG	Enviromental, Social and Governance
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
HRM	Human Resource Management
LM	Lagrange Multiplier
LMM	Linear Market Model
LTA	Liabilities to Assets
MSCI	Morgan Stanley Capital International
NYSE	New York Stock Exchange
OLS	Ordinary Least Square
PROB	Probability Value
QR	Quick Ratio
ROA	Return on Assets
TA	Total Assets
T-LMM	Time-Varying Linear Market Model

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CHAPTER I

INTRODUCTION

This part of the research includes the research problem, purpose, data and methodology, significance, limitations and structure of the study.

1.1. Problem of the Research

Systematic risk, also known as market risk, represents the unavoidable risk tied to overall market fluctuations, which cannot be mitigated through diversification. It arises from multiple sources and can be broadly classified into factors such as economic conditions, financial influences, and market dynamics.

A key source of systematic risk stems from macroeconomic factors, such as interest rates, inflation and exchange rates (Al-Gasaymeh et al., 2021). According to the Capital Asset Pricing Model (CAPM), systematic risk is predominantly shaped by market movements, which are heavily influenced by these macroeconomic variables. Another important source of systematic risk originates from firm-specific factors, especially those linked to corporate governance and operational strategies. For instance, a company's expenditures on advertising and research and development can significantly affect its systematic risk profile (McAlister et al., 2007). Changes in sovereign credit ratings are another significant source of systematic risk. An upgrade to investment-grade status often attracts increased foreign investment and lowers borrowing costs, thereby reducing systematic risk for firms within the affected country. Conversely, downgrades can trigger capital flight and raise the cost of capital, amplifying the systematic risk faced by firms in that jurisdiction (Giovannetti et al., 2013).

Beta coefficient is a return shows the sensitivity of a company's stock return to the market in which the company is located and indicates the systematic risks affecting the stock return (Perold, 2004; Rutkowska-Ziarko, 2022). On the other hand, the firm-specific variables may affect the company's sensitivity to the market; a financially strong company can overcome difficult times more easily and be less affected by systematic risks. Therefore, the idea that there is a relationship between beta coefficient, which is an indicator of systematic risk, and company financials constitutes the main element of this study.

1.2. Aim of the Research

In this research, it is aimed to measure the sensitivity of the companies' financials operating in the industrial, material and energy sectors of the Morgan Stanley Capital International (MSCI) developed countries' markets with the fundamental beta CAPM (the Capital Asset Pricing Model) method. Building on the methodology used in the study by Beaver, Kettler, and Scholes (1970), the relationship between the beta coefficient, a measure of systematic risk, and firm-specific variables was examined.

In the literature, there are many studies on different models of CAPM, and studies on basic beta calculations can be included in these. It is thought that this study will contribute to the literature by expanding the sample by selecting from MSCI countries.

The primary aim of this study is to analyze the impact of financial performance indicators on systematic risk, represented by the beta coefficient. Systematic risk reflects a company's sensitivity to broader market fluctuations. Independent variables include key financial metrics such as dividend payout ratio, acid-test ratio, return on assets, earnings before interest and taxes (EBIT), total assets, liabilities-to-assets ratio, and asset turnover. The research examines annual financial data from 418 companies operating in the energy, materials, and industrial sectors across 18 developed countries, as classified by Morgan Stanley Capital International (MSCI), over the 2016-2023 period.

The study explores how these financial indicators interact with systematic risk, offering valuable insights into the factors that influence a company's exposure to market volatility. By understanding these relationships, investors and decision-makers can develop more effective strategies to assess and manage systematic risk while enhancing financial performance.

1.3.Importance of the Research

This research provides several theoretical and practical contributions:

- **Theoretical Importance:** The study validates the extended use of fundamental beta in capturing systematic risk determinants in developed markets. By integrating firm-specific variables into the CAPM framework, this research highlights the importance of nuanced risk models that reflect the realities of developed economies. This adds depth to the existing body of knowledge and sets a foundation for future studies to explore other sectors and regions.

- **Practical Applications:** For investors, the findings offer a refined approach to assessing risk. By examining firm-specific variables, investors can make informed decisions, especially in developed markets where traditional risk models may fall short. For corporate managers, the results emphasize the importance of strategic decisions in areas such as asset management, dividend policies, and cost structures to mitigate systematic risk.

1.4. Data and Methodology

In this study, the sensitivity of firm-specific variables of companies operating in the industrial, materials, and energy sectors within the Morgan Stanley Capital International (MSCI) developed country markets was intended to be measured using the fundamental beta CAPM (Capital Asset Pricing Model) method. Building on the methodology used in the study by Beaver, Kettler, and Scholes (1970), the relationship between the beta coefficient, a measure of systematic risk, and firm-specific variables (dividends per share, quick ratio, return on assets, earnings before interest and taxes, total assets, liabilities-to-assets ratio, and asset turnover ratio) was examined to determine whether significant effect exist.

In this context, data on firm-specific variables and the systematic risk indicator beta coefficient from a total of 418 companies across 18 developed countries were analyzed using the panel regression method to observe the relationship between the variables. Additionally, a cluster analysis was conducted to assess whether the relationship between the variables differs across countries. As a result of the cluster analysis, the sample used in the study was found to be divided into three main groups based on the variables, and the effects of the variables were evaluated according to these groups.

1.5. Limitations

While this study makes significant contributions, it is not without limitations. Firstly, the focus on the industrial sector in developed markets limits the generalizability of findings to other sectors. Future research could expand the scope to include a more diverse set of industries and geographic regions. Additionally, the reliance on secondary data may have introduced biases related to data accuracy and availability.

Furthermore, this research assumes a linear relationship between firm-specific variables and systematic risk. Non-linear relationships or interactions among variables could provide a more comprehensive understanding. Exploring alternative models, such as machine learning-based approaches, could enhance predictive accuracy and offer richer insights.

Lastly, the study period (2016-2023) represents a specific economic environment. Companies with insufficient or missing data were not included in the sample. Additionally, the year-based restriction is determined by the beta coefficient, which serves as the dependent variable. Extending the analysis to include different time frames, especially during periods of economic crisis or recovery, could offer valuable perspectives on the robustness of the findings.

1.6. Structure of the Study

This thesis is composed of five main sections. The first section provides the introduction. The second section presents the theoretical background in detail, followed by a comprehensive review of the relevant literature. The third section outlines the research methodology, including the methods employed in the study. The fourth section contains the empirical findings. In this part, the sample used in the study is introduced in detail, and the stages of the panel data analysis along with the corresponding findings are presented. The fifth and final section includes the conclusion and recommendations. This section offers a general summary of the study and provides several recommendations based on its limitations.

CHAPTER II

THEORETICAL BACKGROUND AND PREVIOUS RESEARCHES

In this part of the research, the theoretical background will be given in detail. Then, this theoretical background will be supported by a literature review.

2.1. The Modern Portfolio Theory

In the central theme of financial research, the relationship between risk and return were always been (Elton et al., 2014). The importance of this relationship is even dated back to 1738, when the St Petersburg Paradox has been analyzed by Daniel Bernoulli. This paradox is based on quite simple coin bet and has explained that the main aim is not to maximize the welfare of individuals, but to maximize the utility. In this paradox, it is seen that when number of bets increases, then the expected utility level decreases, therefore the concept of ‘’the risk aversion’’ has appeared.

The risk and return trade-off has not been explained numeratically or systematically until 1950’s. In 1952, Harry Markowitz published a paper titled "The Portfolio Selection," in which he grounded these trade-offs on essential mathematical principles. At the heart of Markowitz's theory is the idea that investors always demand to maximize their expected utility while minimizing risk. Expected returns are calculated by using historical performance of assets, while risk is quantified using variance or standard deviation. Markowitz posited that the risk of a portfolio is not merely the sum of the risks of individual assets; rather, it is influenced by the correlations between asset returns. This insight led to the understanding that diversification can reduce overall portfolio risk (Carvalho Silva et al., 2019; He, 2024).

One of the key contributions of Markowitz's theory is the concept of the efficient frontier (Markowitz, 1952). The efficient frontier is a collection of ideal portfolios that maximizing expected return for a specified level of risk or minimizing risk for a given expected return. Portfolios that lie on the efficient frontier are considered efficient, while those that fall below it are suboptimal. The efficient frontier is typically depicted graphically, with risk on the x-axis and expected return on the y-axis (Eom et al., 2015; Qu et al., 2017).

Markowitz emphasized the importance of diversification in portfolio construction. By combining assets that are not perfectly correlated, investors can reduce the overall risk of their portfolios. The theory suggests that the lower the correlations between the assets in a portfolio, the more efficient the portfolio becomes. This principle of diversification is a cornerstone of modern investment strategies and is widely accepted in both academic and practical finance (Montenegro & Albuquerque, 2017; Radović et al., 2018).

According to the Capital Asset Pricing Model (CAPM), a company's total risk is composed of two main types: unsystematic risk and systematic risk (Jagannathan et al., 1995; Sharpe, 1964b). The overall risk is quantified by the variance or standard deviation of stock returns. Arising from firm-specific events such as strikes, product defects, and poor management, unsystematic risk can be mitigated through portfolio diversification (Brealey & Myers, 2003). However, not all investors maintain diversified portfolios, making unsystematic risk a relevant factor that significantly affects stock returns (Van Horne, 2021). On the other hand, systematic risk cannot be avoided even with diversified portfolios. Systematic risk measures the relative volatility of a stock in comparison to the overall market, or the risk of a stock relative to the market portfolio (Brealey & Myers, 2003). This type of risk can fluctuate based on company management and can vary over different time periods. Managerial decisions regarding operations, investments, and financing influence company performance, thereby affecting how its returns correlate with market returns. Consequently, firm-specific variables can provide insight into systematic risk.

Risk is typically related with the likelihood of unfavorable events occurring. However, in the context of investments, risk pertains to the probability of an investor receiving a lower return than anticipated. As a result, all investors requires a rate of return commensurate with the level of risk, with higher relative risk necessitating a higher required rate of return (Fabozzi et al., 2008). In a rational market, there is a positive relationship between risk and performance. In the modern economy, beta, or systematic risk, is frequently used by researchers and analysts to calculate a company's cost of capital, explain individual investment strategies, and evaluate business performance. Given the significant importance of beta for business executives and investors, further analysis is necessary to understand how it is determined (Doğukanlı & Borak, 2018).

2.2. Portfolio Risk and Return

In the finance literature, "the Modern Portfolio Theory" was created by Harry Markowitz (1952) and the general framework of this theory includes investing a certain amount of savings in different securities and keeping this investment in a certain period

(Marling & Emanuelsson, 2012). According to the modern portfolio theory, investors choose portfolios from among different portfolio options in accordance with their risk preferences. Here, besides the risk perception of the investor, there are two issues that need to be dealt with; these are expressed as the return and risk of the portfolio.

The concept of return in portfolio management expresses the absolute increase (return) obtained from a certain amount of investment for a certain period ending. Risk, on the other hand, is defined as the standard deviation of expected returns on an asset in Modern Portfolio Theory.

Risk is typically linked to the chance of an adverse event happening. In investments, however, risk refers to the probability that an investor will receive a lower return than anticipated. Consequently, investors demand a certain rate of return from their trades, and the higher the relative risk, the higher the required rate of return (Ioannis, 2019).

2.3. The Efficient Frontier and Portfolio Selection

A rational investor is always expected to be risk averse. However, the investor has a low variance (risk) and high return expectation for the invested asset (Marling & Emanuelsson, 2012). The problem of choosing the most suitable portfolio among the existing portfolios is as old as the days of stock markets. The mean analysis of variance, derived by Harry Markowitz (1952), has provided a solution to this problem for both researchers and practitioners in the financial sector through simple mathematical formulas. Markowitz suggests choosing the portfolio with the lowest risk for a given average portfolio return level (Bodnar & Schmid, 2009).

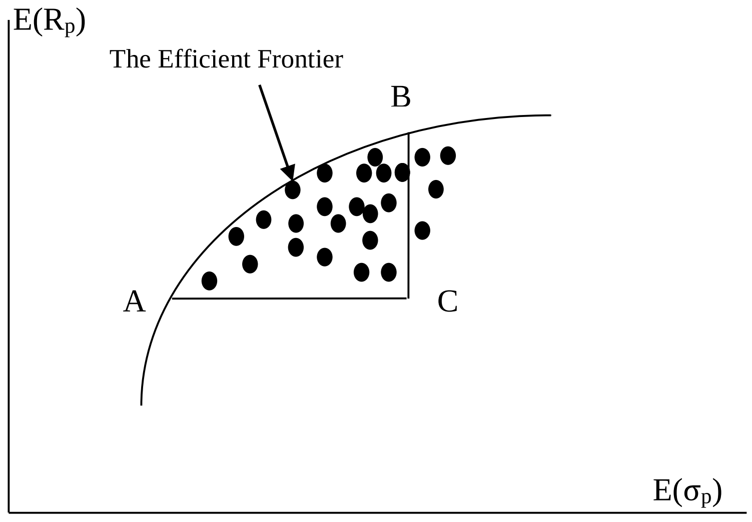

Figure 1. The Efficient Frontier (Doğukanlı & Borak, 2018).

The relationship between the Efficient Frontier and Portfolio Selection is one of the cornerstones of modern portfolio theory, established by Harry Markowitz in the early 1950s. The Efficient Frontier represents a set of optimal portfolios that offer the highest expected return for a given level of risk and, conversely, the lowest risk for a given level of expected return. $\bar{R}_p$ represents expected return of portfolios, when σ_p representing the standart deviations of portfolio returns.

This concept is fundamental to portfolio selection because it provides a framework for investors to make informed decisions about asset allocation based on their risk tolerance and return expectations (Zhang, 2023). Markowitz's pioneering work introduced the idea that investors can construct portfolios that maximize returns while minimizing risk through diversification. The Efficient Frontier is depicted graphically, where the x-axis represents risk (usually measured by the standard deviation of portfolio returns) and the y-axis represents expected return. Portfolios that lie on the Efficient Frontier are considered efficient, as they cannot be improved upon without increasing risk or decreasing return (Jin et al., 2021; Zhang, 2023). This graphical representation allows investors to visualize the trade-offs between risk and return, facilitating more strategic investment decisions.

The inclusion of various asset classes, such as equities, bonds, and alternative investments, can shift the Efficient Frontier. For instance, the addition of cryptocurrencies like Bitcoin has been shown to positively impact the Efficient Frontier by expanding its boundaries and enhancing potential returns without proportionately increasing risk (Batista & Alves, 2021). This illustrates how the composition of a portfolio can significantly influence its efficiency and overall performance. The ability to incorporate diverse asset classes is crucial for investors seeking to optimize their portfolios in a dynamic market environment.

Moreover, the Efficient Frontier is not static; it can be influenced by changes in market conditions, investor preferences, and the introduction of new financial instruments. For example, the introduction of Environmental, Social, and Governance (ESG) constraints in portfolio selection has been shown to create a new Efficient Frontier that reflects sustainable investment practices (Qi & Li, 2020). This adaptation of the Efficient Frontier underscores the importance of aligning investment strategies with broader societal values while still aiming for optimal financial performance.

The mathematical foundation of the Efficient Frontier is rooted in the mean-variance optimization framework, which quantifies the relationship between risk and return. Investors can utilize this framework to derive the Efficient Frontier by solving for the optimal weights of various assets in their portfolios (Cai & Long, 2022; Pandey, 2012) The mean-variance approach allows for a systematic evaluation of potential portfolios, leading to the identification of those that lie on the Efficient Frontier. This process is critical for investors who wish to construct portfolios that align with their specific risk-return profiles.

In real-world applications, the Efficient Frontier acts as a standard for assessing portfolio performance. It allows investors to evaluate their actual portfolio returns against the expected returns of portfolios on the Efficient Frontier, helping them determine whether they are achieving optimal performance relative to their risk tolerance (Evans, 2019). This comparison can inform rebalancing decisions and adjustments to asset allocation strategies, ensuring that portfolios remain aligned with the investor's objectives over time.

Furthermore, the Efficient Frontier is integral to the development of various portfolio optimization techniques, including the use of advanced algorithms and analytical methods. For instance, hybrid approaches that combine genetic algorithms with traditional optimization techniques have been employed to identify portfolios that lie on the Efficient Frontier while considering multiple objectives (Solimanpur et al., 2015). These innovative methodologies enhance the ability of investors to navigate complex investment landscapes and achieve superior outcomes.

The relationship between the Efficient Frontier and portfolio selection also extends to the concept of the Capital Market Line (CML), which represents the risk-return trade-off of efficient portfolios that include a risk-free asset. The CML is derived from the Efficient Frontier and illustrates the benefits of combining risky assets with a risk-free asset to achieve a higher expected return for a given level of risk (Keykhaei & Jahandideh, 2013). This relationship emphasizes the importance of understanding how different asset classes interact within a portfolio and the potential for leveraging risk-free assets to enhance overall portfolio efficiency.

2.4. Systematic & Unsystematic Risk

2.4.1. Systematic Risk

Systematic risk, often referred to as market risk, is an important concept in finance that represents the inherent risk associated with the overall market or a specific segment of the market. Unlike the concept of unsystematic risk, which can be reduced through diversification, systematic risk affects all securities in the market and is driven by macroeconomic factors such as interest rates, inflation, and business cycles. The Capital Asset Pricing Model (CAPM) is one of the most widely used frameworks for measuring systematic risk and is usually measured by the beta coefficient, which indicates the sensitivity of a security's returns to market movements.

The relationship between interest rates and systematic risk is the effect of interest rate fluctuations on the financing decisions of corporate firms. Firms with high levels of debt financing are more sensitive to changes in interest rates than similar firms because higher interest rates increase the firm's interest expenses and may lead to greater financial distress. Lee and Jang emphasize that firms with high debt burdens may have difficulty meeting their short-term obligations, thus increasing their systematic risk and potential bankruptcy risk (Lee & Jang, 2007). This relationship demonstrates the importance of effective financial policies in managing systematic risk, especially for highly leveraged firms. In addition, the interaction between interest rates and systematic risk can be observed in the context of investment decisions. Rofiqoh and Mukaffi (2021) found that interest rates significantly determine the relationship between systematic risk (beta) and stock prices. As interest rates increase, the impact of systematic risk on stock prices becomes more pronounced, and therefore investors need to consider interest rate movements when evaluating the risk-return profile of their investments. From a broader economic perspective, the relationship between interest rates and systematic risk can be seen more clearly. Hodula and Pfeifer (2018) discuss how fiscal and monetary policies affect financial stability, which in turn affects the systematic risk faced by firms. For example, during periods of low interest rates, firms may borrow more, increasing their exposure to systematic risk if economic conditions deteriorate. Conversely, rising interest rates can lead to tighter financial conditions, which can increase systematic risk in the market.

The relationship between inflation and systematic risk can be further complicated by the effects of inflation targeting policies implemented by central banks. Inflation targeting is the stabilization of inflation expectations by central banks of countries in order to reduce uncertainty in financial markets. Walsh (2009) has stated that countries that adopt inflation targeting generally experience better macroeconomic performance, which in turn creates lower systematic risk in such economies. However, on the other hand, the uncertainty that arises when inflation expectations are not fixed can increase systematic risk, as investors demand higher risk premiums to compensate for the perceived increase in risk. It shows that fluctuations in expected inflation and its volatility are critical components of long-term risks affecting asset pricing (R. Bansal & Shaliastovich, 2013). The findings of Bansal and Shaliastovich's studies show that when inflation is volatile, it can lead to increased uncertainty in financial markets, thereby increasing systematic risk. This volatility can manifest itself in various ways, such as affecting consumer confidence, changing investment decisions, and affecting corporate financing strategies.

Geopolitical risks are one of the concepts that determine systematic risk, encompassing national and international issues such as wars, terrorism, and political uncertainty. One study shows that periods of geopolitical tension lead fund managers to adopt more conservative investment strategies (Liu et al., 2024). This behavior reflects a broader trend where investors reassess their portfolios in response to geopolitical events, often leading to increased demand for safer assets and a corresponding increase in systematic risk. Moreover, geopolitical uncertainty can increase firms' debt financing costs. Mokdadi and Saadaoui's study (Mokdadi & Saadaoui, 2023) shows that geopolitical uncertainty – especially during periods of major geopolitical events such as the Russia-Ukraine war – has a significant impact on the cost of debt for firms listed in Germany. This finding suggests that firms operating in high-risk geopolitical environments may face higher borrowing costs, increasing their likelihood of being exposed to systematic risk. The implications of this relationship highlight its importance for corporate financial management as companies must consider the complexities of geopolitical risks when making financing decisions.

2.4.2. Unsystematic Risk

Unsystematic risk, often referred to as firm specific risk, is associated with factors specific to a company or industry, such as management decisions, operational performance, and competitive dynamics. Understanding unsystematic risk is vital for investors and portfolio managers as it directly impacts investment strategies and asset pricing.

Internal firm management is a key determinant of unsystematic risk. Factors such as corporate governance practices, managerial responsibilities, and operational processes can have a direct impact on this type of risk. For instance, Fargher et al. (2001) highlight that technical violations of debt covenants increase the risk of bankruptcy, emphasizing their significance in firm-specific risk assessment. Additionally, the agency problem, defined as the conflict of interest between shareholders and management, plays a crucial role in determining unsystematic risk levels. It is suggested that firms with higher ownership concentration may experience a reduction in unsystematic risk due to stronger alignment in managerial decision-making processes.

Other notable internal factors influencing unsystematic risk include financial performance metrics such as profit margins, earnings reports, and asset management efficiency. Kausar et al. demonstrate that aspects such as market shares and management structure can lead to fluctuations in a firm's unsystematic risk, indicating that careful operational oversight can mitigate risk levels (Kausar et al., 2024). Similarly, Elmomiaty et al. emphasize the need for privately-owned firms to consider unsystematic risks in their valuations, demonstrating that failing to recognize internal inefficiencies can skew valuations despite the inherent diversifiable nature of this risk (Erasmus et al., 2012).

One of the other determinants of unsystematic risk is the decisions made by the company's management. One of the key areas where managerial decisions affect unsystematic risk is executive compensation and incentives. An executive compensation structures can influence managerial behavior, which in turn can affect company risk profiles following mergers and acquisitions (Amewu & Alagidede, 2019). When corporate managers are incentivized to prioritize short-term gains, they may engage in riskier behaviors that increase unsystematic risk, such as underinvesting in long-term projects or overleveraging the firm. This relationship highlights the importance of aligning managerial incentives with long-term value creation to reduce unsystematic risk. Furthermore, concentration of managerial ownership also shapes unsystematic risk. It is discussed in the literature how managers' exposure to unsystematic risk increases as their personal wealth becomes increasingly tied to their firms, due to having an undiversified portfolio (Arugaslan & Jarrell, 2010). This may lead to a misalignment of interests where managers may prioritize their personal financial security over the long-term financial health of the firm, thus potentially increasing unsystematic risk.

Moreover, the role of brand management and human resources management (HRM) practices are also affecting the unsystematic risk in a company. Previous studies showed that a strong consumer-based marketing strategies and effective HRM applications are able to protect firms from unsystematic risks (Park et al., 2013; Rego et al., 2009).

The importance and impact of unsystematic risk are fundamental implications for portfolio management. The more diversified a portfolio is, the lower its unsystematic risk is. Many studies in the literature emphasize that effective diversification can help investors manage unsystematic risk because fluctuations specific to individual securities can be offset by the performance of other assets in the portfolio (Markowitz, 1952). This principle forms the basis of Markowitz's modern portfolio theory (Elton et al., 2014), which assumes that investors can achieve optimal risk-return profiles by holding a diversified mix of assets.

Unsystematic risk pricing affects expected returns from stocks. A study in the literature has shown that unsystematic risks can affect the price stability of financial assets, thus suggesting that investors demand higher returns to take more unsystematic risk (Masry & El Menshawy, 2018). This relationship suggests that unsystematic risk is not just a byproduct of investment, but a critical factor in determining expected returns, especially in emerging markets where company-specific factors can have an impact on stock performance.

The relationship between unsystematic risks and systematic risk was first introduced by Beaver, Kettler, and Scholes in their 1970 study (Beaver et al., 1970). Establishing the relationship between firm-specific variables and the beta coefficient has significantly contributed to a broader understanding of market determined and accounting determined measurements and the examination of their impact on valuation and investment strategies.

2.5. Capital Asset Pricing Model

A set of financial models exists to evaluate the risk-return relationship, enhancing the efficiency of financial decision-making (Roque et al., 2021). The most commonly used among these is the Capital Asset Pricing Model (CAPM). This model assesses the value of financial assets by considering their return and risk, their correlation with the market portfolio, and leveraging stock market data.

One of the fundamental questions in finance literature is how does risk of a financial investment affects the expected return on that asset. In this context, one of the approaches that offers a consistent framework is the Capital Asset Pricing Model

(CAPM). The model was first developed by William Sharpe in 1964; then the same model was studied by Jack Treynor, John Lintner and Jan Mossin at different dates (Sharpe, 1964; Perold, 2004). The calculation of beta coefficient is shown below.

$$\beta_i = \frac{COV_{i,m}}{\sigma_m^2}$$

where:

β_i = Beta coefficient of asset i, measuring its sensitivity to market movements.

$COV_{i,m}$= Covariance between the returns of asset i and the market portfolio m.

σ_m^2 = Variance of the market portfolio returns.

This formula quantifies the systematic risk of a security relative to the market. If $\beta > 1$, the asset is more volatile than the market; if $\beta < 1$, it is less volatile.

2.5.1. Assumptions of CAPM

The Capital Asset Pricing Model (CAPM) is a foundational concept in finance that seeks to explain the relationship between systematic risk and expected return for assets, particularly stocks (Glova, 2014). The model is predicated on several key assumptions that are critical for its theoretical underpinnings and practical applicability.

One of the primary assumptions of the CAPM is that investors are rational and risk-averse, meaning they prefer to maximize their expected utility and will choose portfolios that minimize risk for a given level of expected return. This assumption aligns with the mean-variance optimization framework established by Markowitz, which underpins the CAPM's reliance on the efficient market hypothesis (EMH) (Elbannan, 2014; Hodnett & Hsieh, 2012). Furthermore, the CAPM assumes that all investors have homogeneous expectations regarding future returns and risks, which implies that they will arrive at the same conclusions regarding the risk-return trade-off for any given asset (Dawson, 2015; Liao et al., 2023). This homogeneity is crucial for the model's predictive power, as it leads to a consensus on the market portfolio, which is assumed to be efficient.

Another critical assumption is that markets are including no taxes, transaction costs, or restrictions on short selling (Elbannan, 2014; Hodnett & Hsieh, 2012). This idealized environment allows for the free movement of capital and ensures that all investors can access the same information simultaneously, leading to the conclusion that the market portfolio is the optimal portfolio for all investors. Additionally, the CAPM assumes that investors can diversify their portfolios to eliminate unsystematic risk, leaving only systematic risk, which is measured by beta (Bali & Cakici, 2008; Wei & Zhang, 2005).

This assumption is pivotal because it posits that only systematic risk is rewarded in the form of expected returns, while firm specific risk does not earn a premium since it can be mitigated through diversification.

Moreover, the CAPM is built on the assumption that asset returns are normally distributed, which simplifies the analysis of risk and return (Oseni & Olanrewaju, 2017; Wang et al., 2004). However, this assumption has faced criticism, as empirical evidence suggests that asset returns often exhibit non-normal characteristics, such as skewness and kurtosis (Asthana et al., 2024; Dawson, 2015). This has led to the exploration of alternative models that account for these deviations from normality, such as the Conditional Higher Moment CAPM, which incorporates higher-order moments of the return distribution to better capture the risk-return relationship (Asthana et al., 2024; Barillas & Shanken, 2018).

Lastly, the CAPM assumes that the relationship between risk (as measured by beta) and expected return is linear and stable over time. This linearity is essential for the model's simplicity and ease of use; however, it has been challenged by empirical findings that suggest this relationship may not hold consistently across different market conditions or time periods (Asiedu et al., 2019; Syed Hamid Ali Shah et al., 2021; Ward & Muller, 2012). As a result, researchers have proposed modifications to the CAPM, such as the Intertemporal CAPM (ICAPM), which allows for time-varying risk premiums and acknowledges the potential for changing market dynamics (Chiarella et al., 2013; Wei & Zhang, 2005).

2.6. Different Approaches in Computing Beta Coefficient

2.6.1. Beta According to Standart CAPM

In the model put forward by William Sharpe (1964), the relationship between a dominant factor thought to be effective on a financial asset and the returns of that asset is observed. As a definition, the word systematic risk was used for the first time in this model.

Central to financial risk theory is the beta factor, a coefficient that indicates the relationship between an asset's returns and the returns of the market portfolio. In asset valuation models, the beta coefficient illustrates the risk-return relationship, where a higher level of systematic risk implies greater risk for investors. The beta coefficient can be either greater or less than 1, indicating the sensitivity of the asset to market movements (Roque et al., 2021).

2.6.2. Accounting Beta

Accounting beta is a financial metric that quantifies the sensitivity of a company's return on equity (ROE) to changes in the overall market's ROE. This measure serves as an alternative to the traditional market beta, which is based on stock price movements. By focusing on accounting performance metrics, accounting beta provides insights into how a firm's fundamental financial health correlates with market dynamics. Specifically, it is calculated as the covariance of a firm's ROE with the market's ROE, thereby linking accounting performance directly to systematic risk (Nekrasov & Shroff, 2009).

To calculate accounting beta, profitability ratios can be used instead of market return rates. Market return refers to the relative change in a stock's price over a specific period, which may or may not include dividends. However, the fundamental question is how the profitability of the overall market or sector influences the profitability of an individual company (Rutkowska-Ziarko & Pyke, 2017). The accounting beta coefficient for Return on Assets ($\beta_i ROA$) can be calculated as follows:

$$\beta_i ROA = \frac{COV_{i,m}(ROA)}{\sigma_m^2(ROA)}$$

where:

$COV_{i,m}(ROA)$ shows the covariance between average market portfolio and company i,

$\sigma_m^2(ROA)$ shows the variance of market portfolio (Hill & Stone, 1980).

The significance of accounting beta lies in its ability to assess risk in a manner that is more reflective of a company's operational performance rather than just its stock price volatility. This is particularly useful for investors and analysts who seek to understand the underlying economic factors that drive a company's returns. For instance, demonstrate that accounting beta can effectively measure risk for unlisted companies, where traditional market beta may not be applicable due to the absence of market data (Faiteh & Aasri, 2022). This highlights the versatility of accounting beta as a risk assessment tool across different types of firms.

Moreover, research indicates that accounting beta can provide valuable insights into the risk relevance of accounting variables under varying economic conditions. found that the risk relevance of accounting information has remained significant over time, suggesting that accounting measures continue to play a crucial role in evaluating firm-specific risk (Brimble & Hodgson, 2007). This is further supported by studies that show a strong correlation between accounting-determined risk measures and market-determined risk measures, indicating that accounting variables can serve as predictive indicators of future risk (Jarvela et al., 2009; Parthasarathy, 2019).

In summary, accounting beta is a vital concept in finance that enhances the understanding of a firm's risk profile by linking its accounting performance to market risk. It offers a more nuanced perspective on risk assessment, particularly for firms where traditional market measures may fall short. By incorporating accounting beta into investment analyses, stakeholders can make more informed decisions that reflect both market conditions and the intrinsic financial health of the companies they evaluate.

2.6.3. Fundamental Beta

The market beta measures the relationship between a securities' risk and the market risk, indicating how closely a stock's returns align with those of the overall market portfolio. However, this metric is based solely on historical price movements and does not account for a company's fundamental characteristics.

The concept and application of fundamental beta are based on a paper published by Beaver, Kettler, and Scholes in 1970. In this study, variables such as dividend payout, average asset growth, average leverage, average asset size, average liquidity, earnings variability, and accounting beta were used as independent variables, while the beta coefficient served as the dependent variable (Beaver et al., 1970).

$$B_f = \propto + \sum_{j=1}^{n} \gamma_j X_j + \epsilon$$

where:

B_f = Fundamental beta (estimated systematic risk).

α = Intercept term.

X_j = Firm-specific financial/accounting variables (e.g., earnings variability, financial leverage, asset size, liquidity, and profitability).

γ_j = Coefficients representing the impact of firm-specific variables on beta.

ϵ = Error term.

Fundamental beta refers to a measure of a stock's sensitivity to systematic risk, derived from the underlying economic fundamentals of the company rather than just its historical price movements (Doğukanlı & Borak, 2018). This concept is closely tied to the Capital Asset Pricing Model (CAPM), which posits that the expected return on an asset is proportional to its systematic risk, represented by beta. However, fundamental beta emphasizes the intrinsic characteristics of a firm, such as its earnings and its changes, growth changes, and overall financial health, as determinants of its risk profile and expected returns (Cohen et al., 2009; Refai & Hassan, 2018).

The relationship between fundamental beta and expected returns is a crucial aspect of asset pricing theories. Research has shown that stocks with higher fundamental betas tend to yield higher expected returns, aligning with the principle that investors require compensation for bearing additional risk (Cohen et al., 2009; Refai & Hassan, 2018). This contrasts with traditional beta, which is often calculated based on historical price data and may not adequately reflect the true risk associated with a stock's fundamental characteristics. For instance, highlight that differences in relative price levels of individual stocks can often be explained by their fundamental betas, suggesting that these measures provide a more accurate reflection of a stock's risk-return profile (Cohen et al., 2009).

Moreover, the concept of fundamental beta has implications for portfolio management and investment strategies. By focusing on fundamental betas, investors can potentially identify undervalued stocks that possess strong fundamentals but may be mispriced due to market inefficiencies. This approach aligns with the findings of , who argue that traditional beta may not capture all relevant risk factors, thereby necessitating a broader understanding of the variables influencing asset returns (Downs & Ingram, 2000)

In summary, fundamental beta serves as a critical tool for investors seeking to understand the intrinsic risk associated with stocks based on their economic fundamentals. By integrating fundamental beta into their investment analyses, investors can enhance their ability to make informed decisions that align with their risk tolerance and return expectations.

2.6.4. Versions of CAPM

Definitions for other beta calculations in the finance literature are given in the table below.

Table 1.

Versions of CAPM

Model Name	Writer(s)	Variables Used	Explanation
Standart CAPM	(Sharpe, 1964)	Beta, risk-free rate, risk, market return.	This model is rely on market symmetrical assumptions and information in the market
Reductive-Undesirable CAPM	Hajun & Varoon (1974)	Semi variance measurement and beta in undesirable explained according to Semivariance.	This model may be used when distribution of returns lower or higher than symmetry.
Adjustable CAPM	Nagorniak (1982)	Defining liquidity risk in acquisition investment beta.	Liquidity risk of securities and market liquidity risk
Multiperiod CAPM	Bierman & Smidt (1975)		The investor acts with an investment horizon that covers more than one period.
Conditional CAPM	Jagannathan & Wang, (1996)	Beta is found according to dividing market variance to stock return covariance and market return.	Due to the changes in market, every investor has a different expectations.
Revised CAPM	Roodposhti, (2017)	Compiling the beta of the revised models of capital assets related to the assumptions of operational, financial and economic leverages	Operational, financial and economic risks are not to be taken into account.
Consumption Based CAPM	(Mankiw & Shapiro, 1984)	Beta is defined based on the consumption growth of investors and the market.	Higher level of beta in risky assets are generally indicates that higher expected return.
Rewarding CAPM	Graham Bornholt (2011),	Risk premium average of monthly stock in the last period is divided by risk premium average in the same period	Stock return is a total of expected and unexpected return rates.
Behavioral CAPM	Shefrin & Statman, (1994)	Investors' choices according to different investment opportunities	In this theory, investors constitute their securities portfolio like a pyramid
Extrapolatin CAPM	N. Barberis, R. Greenwood & A. Shleifer (2015)	Expectations of investors related to future returns	Investors' choices are generally relies on the future expectations.

Source: (Roodposhti, 2017). Created manually.

2.7.Firm-Specific Variables and Systematic Risk

2.7.1. Defining Variables

Defining the independent variables separately would help to understand the relationship with systematic risk. In this section, the variables required for the fundamental beta calculation are defined.

2.7.1.1. Liquidity

A fundamental assumption related to the relationship between firm specific variables and systematic risk is the impact of business liquidity on systematic risk. Various financial ratios assess a company's liquidity, including the Current Ratio, Quick Ratio, Cash Ratio, and Operating Cash Flow Ratio. Quick Ratio, which is calculated from the sum of Cash and marketable securities and Trade receivables (net) to Current liabilities. Quick Ratio whether the company's liquid assets can meet the company's liabilities. When the ratio is lower than the unit, then the enterprise cannot cover its liabilities with its liquid assets while if it is larger than the unit then the company is able to pay its liabilities with liquid assets.

The current ratio, defined as the ratio of a company's current assets to its current liabilities, is a key indicator of a firm's short-term liquidity and financial health. A higher current ratio suggests that a firm is better positioned to meet its short-term obligations, which can lead to a perception of lower risk among investors. Consequently, firms with higher current ratios may exhibit lower beta values, reflecting reduced sensitivity to market fluctuations (Mallik et al., 2022). This relationship indicates that firms with strong liquidity positions are perceived as less risky, which can stabilize their stock prices and reduce their beta.

Research has shown that liquidity ratios, including the current ratio, significantly influence systematic risk. For instance, a study analyzing various performance measures in the cement industry found that liquidity ratios had a statistically significant relationship with beta, suggesting that firms with better liquidity profiles tend to have lower systematic risk (Mallik et al., 2022). This finding aligns with the notion that strong liquidity can mitigate financial distress, thereby reducing a firm's exposure to market volatility.

The quick ratio, also known as the acid-test ratio, is a more stringent measure of liquidity than the current ratio, as it excludes inventory from current assets. This ratio assesses a firm's ability to meet its short-term liabilities with its most liquid assets. Similar to the current ratio, a higher quick ratio indicates better liquidity and financial stability, which can lead to a lower beta (Kim et al., 2007). Firms that can quickly convert their assets into cash are generally perceived as less risky, resulting in reduced sensitivity to market movements.

Studies have indicated that the quick ratio, along with other liquidity measures, plays a significant role in determining a firm's systematic risk. For example, research examining the determinants of systematic risk in various industries has found that liquidity ratios, including the quick ratio, are statistically significant predictors of beta (Kim et al., 2007). This suggests that firms with strong liquidity, as indicated by a high quick ratio, are less likely to experience extreme fluctuations in their stock prices, thereby exhibiting lower beta values.

2.7.1.2. Dividend Payout

The relationship between dividend payout and the systematic risk indicator beta is a nuanced area of financial analysis that has implications for both corporate finance and investment strategies. Beta measures the sensitivity of a stock's returns to the overall market returns, thus serving as an indicator of systematic risk. Understanding how dividend policies influence beta can provide insights into a firm's risk profile and investor expectations.

One of the primary observations in the literature is that higher dividend payouts are often associated with lower beta values. This relationship can be attributed to the signaling effect of dividends. When a company increases its dividend payout, it may signal to investors that the firm is confident in its future earnings stability and cash flow generation. Consequently, this perception of reduced risk can lead to a lower beta, as investors view the firm as less sensitive to market fluctuations (Biza-Khupe & Themba, 2016). For instance, research has indicated that firms with stable and predictable dividend policies tend to exhibit lower volatility in their stock prices, which translates to a lower beta. High dividend payouts tend to negatively impact systematic risk because investors view the consistent flow of dividends as more reliable than potential gains from stock price increases (Logue & Merville, 1972). Gu and Kim (1998) identified an inverse relationship between high dividend payouts and systematic risk. Earlier research also showed that higher dividend payouts reduce systematic risk (Beaver et al., 1970; Breen & Lerner, 1973; Gu & Kim, 1998). The dividend payout ratio is used to measure dividend payout levels.

Conversely, firms that maintain low or irregular dividend payouts may be perceived as riskier. This perception can arise from the notion that such firms may be reinvesting profits into high-risk projects or may be facing financial difficulties that prevent them from distributing dividends. As a result, these firms may exhibit higher beta values, reflecting greater sensitivity to market movements (Sari, 2018). This dynamic suggests that dividend policy serves as a mechanism through which firms communicate their risk profiles to investors.

The relationship between dividend payout and beta can also be influenced by the firm's capital structure. Research has shown that firms with higher leverage tend to have higher betas, as the financial risk associated with debt increases the overall risk profile of the firm (Kapoor et al., 2010). In this context, if a highly leveraged firm decides to increase its dividend payout, it may signal to investors that the firm is confident in its ability to manage its debt obligations, potentially leading to a decrease in beta. However, if the firm is unable to sustain its dividend payments due to high leverage, this could exacerbate perceptions of risk and lead to an increase in beta (Kapoor et al., 2010).

Additionally, the impact of corporate governance on dividend policy can also play a role in shaping the relationship between dividend payout and beta. Studies have indicated that strong corporate governance can lead to higher dividend payouts, as it aligns the interests of management with those of shareholders (Abor & Fiador, 2013). Firms with effective governance structures are often perceived as less risky, which can contribute to lower beta values. Conversely, firms with weak governance may exhibit erratic dividend policies, leading to higher perceived risk and, consequently, higher beta (Abor & Fiador, 2013).

Moreover, the relationship between dividend payout and beta may vary across different sectors and economic conditions. For instance, in industries characterized by high volatility, such as technology or biotechnology, firms may opt for lower dividend payouts to retain earnings for growth opportunities. In such cases, the lack of dividends may signal higher risk, resulting in elevated beta values (Harada & Nguyen, 2011). Conversely, in more stable industries, such as utilities or consumer staples, firms may maintain higher dividend payouts, which can correlate with lower beta values due to the perceived stability of their cash flows (Ullah et al., 2016).

2.7.1.3. Profitability

The relationship between profitability ratios and the systematic risk indicator beta is a critical area of inquiry in finance, as it helps investors and analysts understand how a firm's profitability can influence its exposure to market risk. Beta measures the sensitivity of a stock's returns to the overall market returns, thus serving as an indicator of systematic risk. Various profitability ratios, such as Return on Assets (ROA) and Return on Equity (ROE), can significantly impact beta, reflecting the interplay between a firm's financial performance and its perceived risk.

Numerous studies have previously identified a connection between business profitability and systematic risk. Researchers such as Borde (1998), Gu and Kim (1998), Logue and Merville (1972), Allozi and Obediat (2016), and Scherrer & Mathison (1996) have documented a negative correlation between profitability and betas, suggesting that higher profitability can help firms mitigate financial volatility. This body of work indicates that stable operating cash flows, which lower systematic risk, are influenced by a company's effective management of its profitable assets.

Conversely, Borde, Chambliss, & Madura (1994) discovered a positive relationship between profitability and beta. They found that sectors like finance and insurance, where profitability often involves greater credit risk, exhibit higher risk-taking behavior.

2.7.1.4.Size

The scale of a company is indicative of its size, and there has been considerable research on the relationship between company size and systematic risk. Many studies suggest a negative correlation between business size and the systematic beta risk factor, proposing that larger businesses can achieve economies of scale, thereby reducing unit costs and minimizing risk. Contrary to this, Bowman (1979) argues that systematic risk is not influenced by company size, but rather by capital structure alone. He posits that expanding a business through new investments does not alter the capital structure, thus there is no connection between systematic risk and company size.

Lee and Jang (2007) present a different perspective, finding a positive relationship between systematic risk and the size of airlines in the US, suggesting that larger airlines face greater market risks. Additionally, Daves et al. (2000) note that empirical studies indicate a shift in risk trends: before 1980, smaller firms exhibited higher systematic risk compared to larger ones, while post-1980, larger firms showed greater risk. This shift is interpreted as a result of larger companies making bigger investments or having higher debt-to-equity ratios. Furthermore, Fisher (1959) suggests that securities of large businesses are considered highly marketable and easily convertible to cash, making them less risky. Additionally, larger firms are generally better equipped to absorb economic, social, and political impacts. Amato and Amato (2012) noted that larger firms tend to have lower beta coefficients, reflecting their ability to absorb market shocks better than smaller firms. This finding aligns with the notion that larger firms benefit from diversification and stability, which reduces their systematic risk. Therefore, it can be stated that there are differing views in the literature regarding the impact of firm size on systematic risk.

2.7.1.5.EBIT (Earning Indicator)

Business growth is often evaluated through increases in assets, revenues, or profits. Kim et al. (2002) used annual percentage changes in total assets as a measure of business growth. Other studies have approximated growth rates using annual percentage changes in earnings before interest and taxes (EBIT) (Borde, 1998; Gu & Kim, 1998; Lee & Jang, 2007). Profit-based business growth, as observed by Logue and Merville (1972), tends to be weak during economic fluctuations. Rapidly growing businesses require more resources, prompting them to seek external financing, which can lead to higher leverage and increased systematic risk. Thus, high growth might negatively correlate with systematic risk.

However, another perspective suggests that companies with high profit growth rates can sustain their share prices due to anticipated future profits. Bowman (1979) found a positive relationship between business growth and systematic risk. Logue and Merville (1972) argue that an increase in assets typically leads to increased profits, attracting competitors and heightening sensitivity to financial fluctuations. From an internal viewpoint, it is demonstrated that systematic risk is positively associated with business development, as firms often seek external funding for growth, thereby increasing systematic risk. Conversely, Moyer and Chatfield (1983) discovered a negative relationship between systematic risk and earnings growth. They interpret this to mean that investors view rising profits as a sign of effective risk management, whereas companies with low or negative growth might struggle to manage risk effectively.

2.7.1.6. Financial Leverage

Financial leverage enables companies to expand their operations by utilizing debt financing to enhance their capital structure. Borrowing is the key method for raising capital. Generally, an increase in financial leverage enhances the return on equity ratio, as businesses use borrowed funds to finance operations. However, while financial leverage can provide benefits, it also raises risk. Unlike equity, borrowed funds come with fixed repayment terms, and failing to meet these commitments can lead to financial loss.

The relationship between leverage and systematic risk is an important consideration. Modigliani and Miller (1958) argue that in a perfect capital market without influencing factors, a company's capital structure is largely irrelevant. However, many real-world factors make a business's financial structure crucial. To assess financial leverage, researchers like Moyer and Chatfield (1983) and Kim et al. (1998) have used the debt-to-equity ratio, which measures the proportion of borrowed funds to equity.

Theoretically, investing in a company with a high debt-to-equity ratio is considered risky, particularly if interest rates rise. Empirical studies, such as those by Borde (1998), suggest a positive relationship between leverage and systematic risk, indicating that higher leverage generally correlates with increased systematic risk.

Qizam (2017) conducted a study on the Indonesian Stock Exchange, exploring the causality between financial leverage and systematic risk. The findings indicated a bidirectional relationship, where high levels of beta can lead to increased financial leverage, and conversely, high financial leverage can result in elevated beta levels. This suggests that firms with greater systematic risk may opt for higher leverage to enhance returns, while those with high leverage may be perceived as riskier, thus exhibiting higher beta coefficients.

Aharon & Yagil (2019) examined the impact of financial leverage on shareholders' systematic risk. Their research highlighted that an increase in financial leverage is associated with a rise in the beta coefficient, indicating higher systematic risk. This relationship is particularly pronounced in firms with risky debt structures, where the financial distress costs associated with high leverage can exacerbate the volatility of returns, leading to higher beta values.

2.7.1.7. Efficiency

The ratio of total revenue to total assets serves as a measure of operating efficiency. Businesses that optimize their asset use are more likely to be profitable and less prone to losses. Empirical studies suggest that companies effectively utilizing their assets can mitigate potential losses from previous years, thereby reducing systematic risk. Asset turnover reflects the amount of sales generated for each euro of assets owned by the firm.

Operating efficiency highlights a business's ability to manage its assets effectively. According to Borde (1998), a high-performing company is typically at lower risk due to excellent asset management. However, he also notes that high profitability could result from an aggressive business strategy that may increase risk, such as rapidly boosting sales without stringent cost control (Gu & Gao, 2000).

Two key ratios used to assess efficiency are the asset turnover ratio (sales to total assets) and the fixed asset turnover ratio (sales to fixed assets). These ratios measure revenue generated per dollar of total and fixed assets, respectively. Higher turnover ratios indicate greater efficiency, as they show the business generates more revenue per unit of assets. It has been observed that turnover ratios can vary across different sectors.

2.7.2. The Relationship Between Firm Specific Variables and Systematic Risk

The relationship between financial ratios and the systematic risk indicator, beta, is a critical area of analysis in finance, particularly in understanding how various financial metrics can influence a firm's exposure to market risk. Beta, as a measure of systematic risk, indicates how much a stock's price fluctuates in relation to the overall market. Understanding the interplay between financial ratios—such as profitability, liquidity, leverage, and efficiency—and beta can provide valuable insights for investors and financial analysts.

One of the primary financial ratios that significantly impacts beta is the leverage ratio, which reflects the degree to which a company is financed by debt. Research has shown that firms with higher leverage tend to exhibit higher beta values. This is largely because leveraged firms are more sensitive to market fluctuations; as their fixed financial obligations increase, so does their risk profile Baker et al. (2020). For instance, a study on companies listed on the Newconnect Alternative Exchange found that financial ratios related to net working capital and leverage directly influence the beta coefficient, indicating that investors assess risk similarly across different company sizes and stages of development (Bolek, 2019). This suggests that leverage is a crucial financial ratio to consider when evaluating a firm's systematic risk.

Profitability ratios, such as Return on Assets (ROA) and Return on Equity (ROE), also play a significant role in determining beta. Firms that demonstrate higher profitability are generally perceived as less risky, leading to lower beta values. This relationship is supported by findings that indicate a negative correlation between financial debt ratios and profitability, suggesting that firms with higher debt levels may experience reduced profitability, which in turn can elevate their beta (Tahir & Anuar, 2016). The implication here is that as profitability increases, the systematic risk associated with the firm decreases, making it a vital financial indicator in the context of beta analysis.

Liquidity ratios, such as the current ratio and quick ratio, are another set of financial indicators that can influence beta. Firms with higher liquidity are often viewed as less risky because they have a greater ability to meet short-term obligations, which can lead to a lower beta (Mallik et al., 2022). For example, a study evaluating various performance measures in the cement industry found that liquidity, alongside solvency and asset efficiency, had a statistically significant relationship with beta (Mallik et al., 2022). This highlights the importance of liquidity as a financial ratio that can mitigate systematic risk.

Operational efficiency ratios, such as inventory turnover and asset turnover, also contribute to the understanding of beta. Efficient firms that manage their assets effectively tend to have lower betas, as they are better positioned to withstand market volatility. The relationship between operational efficiency and beta suggests that firms that can convert their assets into sales more effectively are perceived as less risky by investors, thereby exhibiting lower sensitivity to market movements (Mallik et al., 2022). This relationship underscores the importance of operational metrics in assessing a firm's systematic risk profile.

Moreover, the relationship between financial ratios and beta can be influenced by external factors, such as market conditions and economic cycles. For instance, during periods of economic downturn, firms with higher leverage may experience a more pronounced increase in beta, reflecting heightened sensitivity to market risks (Gajurel et al., 2020). Conversely, in stable economic conditions, the impact of financial ratios on beta may be less pronounced, indicating that the context in which these ratios are evaluated is crucial for understanding their relationship with systematic risk.

2.8. Literature Review

2.8.1. A Standart CAPM Measurement

The Capital Asset Pricing Model (CAPM) has long been a staple in the financial economics literature and provides a framework for understanding the relationship between risk and expected return. The classical method of measuring CAPM is based on the linear relationship between an asset's expected return and its systematic risk, represented by beta. After the first development, the model has undergone extensive empirical testing and methodological refinements over the decades. Existing literature has attempted to clarify the assumptions of the CAPM and validate its applicability across a variety of markets and conditions, and has highlighted both the strengths and limitations inherent in its classical formulation.

Research on systematic risk is grounded in the Capital Asset Pricing Model (CAPM) as outlined by Lintner (Lintner, 1965) and Sharpe (1964), (1972). The CAPM posits that the expected return on a risky asset is determined by adding a risk premium to the risk-free rate, with the expected risk premium being directly proportional to beta in a competitive market (M. H. Chen, 2003; Gençay et al., 2003; Lintner, 1965; Sharpe, 1964b; Sheel, 1995).

One of the critical aspects of the CAPM is its reliance on a linear relationship between expected returns and beta, which has been examined in several studies. For example, Taussig (2022) provides a comprehensive analysis of the 57-year validity of the CAPM using traditional regression techniques along with Amihud's daily beta estimate and the Generalized Method of Moments (GMM). The sample data used in related study includes 177,374 firm-year observation and firm data gathered from the Center for Research in Securities Prices (CRSP). The study finds strong significance in the linear nonparametric estimate while rejecting parabolic relationships, reinforcing the basic premise of the CAPM of a linear risk-return relationship. This finding is consistent with the work of Jegadeesh et al. (2019) who used an instrumental variable (IV) approach to test various asset pricing models, including the CAPM, and confirms that the risk premiums associated with these models are reliably different from zero.

Furthermore, the applicability of CAPM has been tested in various markets including emerging economies. Chen (2022) investigated the importance of CAPM in the Chinese stock market, highlighting its historical importance and the difficulties encountered in empirical validation. The study highlights that although CAPM is a fundamental model in asset pricing, its assumptions may not be universally valid, especially in markets characterized by different behavioral and structural dynamics. This finding is also highlighted by Raza et al. (2019) who investigated the downside risk-adjusted CAPM. The related study referred to stock markets of BRICS countries and Pakistan. Results shows that the traditional CAPM's assumptions about systematic risk may not adequately capture the complexities of emerging markets, where the relationship between risk and return may be negative and insignificant.

The classical CAPM measure, besides its simplicity, also has limitations. Bossaerts et al. Bossaerts et al. (2007) argue that although the CAPM serves as a suitable starting point for understanding market dynamics, it can be improved by including additional factors reflecting the demand functions of individual traders. This perspective suggests that the CAPM can be extended to a more detailed model, called CAPM+, that takes into account behavioral aspects and market imperfections. Such extensions are crucial in addressing the criticisms that the CAPM cannot fully explain observed market phenomena, especially in the context of firm specific risks which is highlighted (Hwang et al., 2012). Hwang used a sample of firms listed in FTSE 100 index, data from 1996 to 2007. The results shows that due to the positive intercepts in most portfolios in the selected sample and there are large proportions of firm specific risk, the CAPM is rejected and misspecified.

The CAPM’s core assumptions have been challenged by empirical evidence suggesting that market behavior often deviates from the model’s predictions. For example, Ray et al.’s (2009) study revisits the CAPM, emphasizing its centrality to the asset pricing literature while acknowledging the significant research efforts aimed at its empirical validation. The findings suggest that while the CAPM remains influential, its empirical shortcomings warrant continued scrutiny and adaptation to contemporary market realities.

In addition to theoretical criticisms, the practical applications of the CAPM continue to evolve. For example, study by Siahaan (2018) demonstrate the effectiveness of the CAPM in predicting stock returns compared to alternative models such as Arbitrage Pricing Theory (APT). Their findings suggest that the CAPM, despite its criticisms, remains relevant in certain contexts, particularly in medium- and long-term forecasting.

Another exemplary study on CAPM is conducted by Fama and French (2004), who addresses the theoretical foundations of the model and provides empirical evidence supporting its predictions. The study emphasizes that CAPM establishes a linear relationship between the expected return of an asset and its beta, a measure of its sensitivity to market movements. This relationship has been validated by numerous empirical tests, including those conducted by Black, Jensen, and Scholes (Thilakarathne & Jayasinghe, 2014), who provided evidence for the validity of CAPM by showing a positive correlation between beta and average returns in a diversified stock portfolio.

For Karachi Stock Exchange, downside-risk based beta was calculated by using monthly closing prices between January 2000 to December 2012 (Rashid & Hamid, 2015). The standart beta, upside and downside betas were tested to explain the validity of risk premium. The results indicates that downside risk based beta provides the negative risk premium when the other models shows the positive risk premium. This ampirical result includes significance for investors who wants to create effective investment strategies.

Alves (2023) used a Bayesian minimization approach to estimate the CAPM model with multiple instruments. This methodology is particularly useful for contexts where traditional estimation techniques may suffer from overfitting or multicollinearity. By applying this approach, the study aimed to increase the robustness of CAPM estimates and provide better performance in multifactor risk models.

Chen et al. (2020) proposed an augmented higher-order CAPM (AH-CAPM) that includes higher-order moments and co-moments from the joint distributions of stock portfolio returns and market returns. Both Chinese and US markets are used as samples in the research model and showed that including higher-order moments can improve the explanatory power of CAPM, especially in capturing the behavior of asset returns under different market conditions.

An empirical comparison between agency-based 3 factor model and CAPM model was made by Blitz (2014). In the research, monthly stock level data period have used between July 1926 until December 2010. The results indicates that agency based 3 factor model is better to explain the performance of portfolios in NYSE, AMEX and NASDAQ stock exchange markets.

2.8.2. CAPM Versions According to Other Approaches

Beta, therefore, offers valuable insights for investors and company managers regarding a firm's financial, operational, and investment strategies. Investors use beta to gauge how a firm is influenced by macroeconomic conditions, as its stock returns reflect the company's current and potential earning power in relation to broader economic scenarios (Logue & Merville, 1972). Additionally, beta is expected to interact with a firm's financial and operational policies, which in turn affect market perceptions and ultimately corporate returns and risk (Breen & Lerner, 1973). Thus, beta reflects the market's assessment of a firm's financial, marketing, and production strategies compared to other firms within the macroeconomic context (Logue & Merville, 1972). This study focuses on the relationship between systematic risk and the financial behaviors of US airlines, as financial policies can encompass marketing, production, and operational decisions (Logue & Merville, 1972).

Numerous earlier studies have empirically investigated the relationship between market betas and various accounting variables, such as the debt-to-equity ratio, dividends, growth, and accounting beta.

In their 1970 empirical study, Beaver, Kettler, and Scholes investigated whether accounting variables—payout ratio, growth, leverage, liquidity, size, earnings variability, and accounting beta—could serve as proxies for the total variability of market returns. Analyzing a sample of 307 firms across two periods, 1947-1956 and 1957-1965, they found that the degree of association between accounting betas and market betas was 44 percent and 23 percent for the respective periods. When the analysis was conducted on a portfolio basis, the results improved significantly, with the associations rising to 68 percent and 46 percent, respectively (Beaver et al., 1970).

Ball and Brown (Brown & Ball, 2016) assessed the effectiveness of accounting measures of risk—specifically operating income, net income, and earnings per share—in communicating a firm's risk to the market. Using regression analysis on a sample of 261 firms from 1946 to 1966, they concluded that around 35 to 40 percent of the cross-sectional variability in systematic risk could be explained by the comovement in firms' accounting income.

The first studies on determining whether financial assets are priced correctly were carried out by Black, Jensen and Scholes (1972), Sharpe and Cooper (1972) and Fama and French (1992).

Sharpe and Cooper (1972) examined the relationship between the realized returns and beta values of stocks by using the betas of stocks traded on the New York Stock Exchange (NYSE), using 60-month data between 1931 and 1967. According to the results of the research, approximately 95% of the changes in the expected returns of the traded stocks can be explained by the differences in beta values.

Time-varying beta was measured (Groenewold & Fraser, 1999) for 23 sectors in the Australian market with the help of monthly data between 1979 and 1994. According to the results of the research, betas of stocks, change over time and are not stationary.

With the help of data from real estate companies offered to the public in Turkey (Altınsoy et al., 2010), it has been observed how betas change over time. The sample period of the research consists of seven years of daily data. According to the research findings, the betas of the real estate companies in the sample decrease over time. Another result is that the returns of real estate companies closely follow the stock market.

In another study (Köseoğlu & Mercangöz, 2013), it was desired to test the Zero Beta CAPM developed by Black (1972) on the stocks traded in the Istanbul Stock Exchange 100 Index. In the research findings, it has been determined that both standard CAPM and Zero Beta CAPM models are valid for ISE100 companies and Zero Beta CAPM gives more meaningful results for this sample.

In the study of Bengitöz and Umutlu (2014), the validity of the conditional Capital Asset Pricing Model (CAPM), which allows the beta to change over time, and the static CAPM, where the beta is considered fixed, were tested in ISE100. Unlike other studies on ISE100, in conditional CAPM tests, it is calculated using daily return data within the beta month. To test the consistency of the results, floating betas were also calculated as moving betas using the previous twenty-four months' return data. As a result, it was determined that static and conditional CAPM is not valid in ISE100. In addition, the sample was divided into pre-crisis, crisis and post-crisis periods, and tests were carried out for these sub-periods. The results obtained for the sub-periods also support all sample results. On the other hand, it was found that the price-book value ratio had a significant effect on the average stock return.

In the study conducted by Akbulaev et al. (2016), CAPM was tested using monthly returns between 2005 and 2015 with 10 stocks traded in ISE100. As a result of the research, the beta coefficients of the portfolios created with the stocks included in the sample were found to be less than 1, and these portfolios were evaluated according to the risk sensitivity of the investors.

In another study (Çömlekçi & Sondemir, 2018), it was tested whether the financial asset pricing model is valid in Islamic finance .In this study, the data of 27 companies included in the KATLM-30 Index were selected from the years 2011-2016. According to the research findings, it has been determined that the Islamic Financial Asset Pricing Model (I-CAPM) is applicable for the participation index.

Hatipoğlu (2020) investigated whether the beta coefficients change in the long-term in the member country stock markets in his study, which included the sample of the Gulf Arab Countries Cooperation Council countries. According to the research findings, the monthly beta values of the member countries' stock exchanges showed a significant difference compared to the long-term beta values.

In the research of Neslihanoğlu and Paker (2021), for modeling the foreign exchange portfolios to be created by foreign exchange investors in Turkey and making future forecasts; As the basic model, it used the Linear Market Model (LMM), which allows for stable beta risk consistent with the CAPM. The performance of CAPM is compared with the Time-varying Linear Market Model (T-LMM), which allows for beta risk that is consistent with the Conditional Capital Asset Pricing Model (C-CAPM) and changes over time. As a sample, Turkish Lira (TL) prices of the last 15 years' weekly exchange rates of 9 countries, which are subject to effective buying and selling at the Central Bank of the Republic of Turkey (CBRT), were used. In conclusion, if T-LMM is modeled, it outperforms others in modeling exchange rates and forecasting the future; However, when T-LMM is modeled with GARCH and DCC-GARCH, it was found to be insufficient compared to LMM. It is concluded that beta risks in exchange rates are not stationary.

Grullon et al. (2002) used information on dividend distributions of companies traded on the New York Stock Exchange (NYSE) between 1967 and 1993. They found that companies that pay dividends and increase their dividends experience a significant decrease in systematic risk. This suggests that higher dividend payments may signal stability and lower risk to investors who buy the company's stock, which may lead to a decrease in beta.

Kapoor et al. (2010), in their study, investigated the relationship between dividend payout and systematic risk using data from the Centre for Monitoring Indian Economy (CMIE) database for the period 2000-2008. The study findings showed that dividend payout is inversely related to beta and firms with higher beta values tend to pay lower dividends. This relationship explains that firms with higher systematic risk may prefer to retain earnings rather than pay dividends to finance growth opportunities.

The relationship between the quick ratio and beta coefficient is a particular area that could help to understand how liquidity may effect the firm’s systematic risk. For example, in study made by Raza et al. (2023), variables from 25 cement firms listed in Pakistan Stock Market from 1997-2022 have used. Research findings suggest that firms with a stronger quick ratio are less sensitive to market fluctuations. This finding aligns with the idea that firms with better liquidity positions are perceived as less risky by investors, which may lead to a lower beta coefficient.

Farhan et al. (2019) investigated the impact of liquidity ratios including quick ratio on financial performance in the pharmaceutical industry. The research findings show that liquidity ratios significantly affect financial performance, which in turn can indirectly affect beta; firms with strong liquidity positions may be perceived as less risky, leading to lower beta coefficients.

The consumption based CAPM (Ccapm) has been widely used in finance literature. In the article made by Chen (2003) the comparison between classical CAPM and CCapm approaches was measured for emerging Taiwan stock market. The findings suggests and strongly supports the relationship between stock returns and beta coefficient, also CCapm failed to explain the related market. In another work related to CCapm (Shapiro & Mankiw, 1985), the idea of better implication of CCapm in the markets have experienced. A cross section of 464 stocks have examined and the results shows that with the respect to consumption growth, beta measured with a respect to stock market index outperforms.

Lettau and Ludvigson (2001) studied related to the relationship between wealth, consumption and expected returns. By using time series analysis, they found that consumption-wealth ratio is significantly explains the variations in asset risk and enhancing the explanatory power of traditional asset pricing models. An another study (Parra-Alvarez et al., 2022) investigated the implications of rare events within the framework of the CCapm. Using both analytical methods and simulations, they show how including rare economic disasters in the model leads to more reasonable parameter estimates and reduces the pricing errors observed in empirical data. Their results suggest that accounting for these rare events can significantly increase the explanatory power of the C-CAPM.

2.8.3. Fundamental Beta Literature

In their seminal 1970 study, Beaver, Kettler, and Scholes examined the relationship between accounting-determined risk measures and market-determined risk measures. Analyzing a sample of firms over a specific period, they employed regression analysis to assess how accounting variables could predict systematic risk, laying the foundation for subsequent research in this area (Beaver et al., 1970).

Building upon this foundation, Rosenberg and McKibben (1973) analyzed a sample of 500 U.S. firms listed on the New York Stock Exchange (NYSE) from 1955 to 1970. Using cross-sectional regression analysis, they discovered that accounting-based betas, derived from variables such as earnings volatility and profitability measures (e.g., Return on Assets and Return on Equity), exhibited greater stability over time compared to traditional market betas. This finding suggested that incorporating accounting information could enhance the prediction of systematic and specific risk in common stocks.

Similarly, Lev and Kunitzky (1974) investigated 400 U.S. manufacturing firms between 1960 and 1972, employing pooled panel regression methods. Their study revealed a negative correlation between liquidity ratios (such as the current ratio and acid-test ratio) and fundamental beta, indicating that firms with higher liquidity levels tended to exhibit lower systematic risk. This underscored the importance of liquidity management in mitigating a firm's exposure to market fluctuations.

Hamada (1972) explored the impact of financial leverage on systematic risk by analyzing a sample of firms over a specified period. Utilizing regression analysis, the study found that higher leverage ratios were associated with increased beta coefficients, highlighting the role of capital structure in influencing a firm's market risk.

Expanding the scope, Fama and French (1992) examined the joint roles of market, firm size, and book-to-market equity in determining average stock returns. Analyzing a broad sample of U.S. firms, they employed cross-sectional regression techniques and found that firm size and book-to-market equity were significant determinants of systematic risk, challenging the traditional CAPM model and suggesting that these variables capture dimensions of risk not accounted for by beta alone.

Basu (1983) investigated the relationship between earnings yield and systematic risk by analyzing a sample of firms over a specific timeframe. Using regression analysis, the study found that firms with higher earnings yields tended to have lower beta coefficients, suggesting that earnings performance is inversely related to market risk.

Lastly, Estrada (2002) applied the fundamental beta concept to emerging markets by analyzing a sample of firms from various developing countries. Employing regression analysis, the study found that accounting-based betas were more reliable predictors of systematic risk in emerging markets, where market inefficiencies and data limitations often hinder traditional beta estimation methods.

CHAPTER III

RESEARCH METHODOLOGY

This section explains the methods used and followed in the research. Information on panel data analysis is included in this section.

3.1. Panel Data Analysis

Panel data corresponds to observations across several units over a series of time periods. Consequently, observations in panel data are a combination of two dimensions: the cross-sectional dimension indicated by the subscript "i" and the time dimension indicated by the subscript "t". This structure leads to more complex clustering in panel data. Cross-sectional data includes units such as individuals, countries, firms, and households. In panel data, the degree of multicollinearity among variables decreases, the increased number of observations enhances degrees of freedom, and thereby, efficiency is achieved (Gujarati, 2016).

The method known as "panel data analysis" offers more comprehensive data compared to solely using cross-sectional or time series data, facilitating the modeling of the complexities of human behavior and allowing for the analysis of intricate relationships. In cross-sectional data, multiple units are observed within a single time period, while time series data provides information across multiple time periods for a single unit. When a study aims to encompass both periods and units, panel data methods are the most appropriate choice (Tatoğlu, 2016).

Panel data analyses consist of the combination of time and unit dimensions. Generally, the time dimension is denoted by T, while the unit dimension is represented by N. Typically, the number of units exceeds the number of time periods ($N > T$).

$$Y_{it} = \alpha_{it} + \beta_{1it}X_{1it} + \cdots + \beta_{Kit}X_{Kit} + \mu_{it}\ ,\ i = 1,2, \dots , N,\ t = 1,2, \dots , T$$

In this model, the dependent variable is represented by Y and the independent variables by X. The constant term is denoted by α, the slope parameters by β, and the error term by μ. The subscript i denotes units such as individuals, cities, countries, or firms, while the subscript t represents time periods such as days, months, or years. The distinguishing feature of panel data sets compared to other data sets is the presence of two subscripts simultaneously.

3.1.1. Models of Panel Data

Panel data models are categorized into five different groups based on the values that parameters take according to units and/or time (Safkan, 2020).

Model where both constant term and slope parameters are constant in unit and time:

$$Y_{it} = \beta_0 + \sum_{i=1}^{K} \beta_k X_{kit} + \mu_{it} \ , \ i = 1,2,\dots,N, \ t = 1,2,\dots,T$$

Model where the slope parameter is constant and the constant term varies from unit to unit:

$$Y_{it} = \beta_{0i} + \sum_{i=1}^{K} \beta_k X_{kit} + \mu_{it} \ , i = 1,2, \dots , N, t = 1,2, \dots , T$$

Model in which the slope parameter is constant and the constant term varies according to unit and time:

$$Y_{it} = \beta_{0i} + \sum_{i=1}^{K} \beta_k X_{kit} + \mu_{it} \ , i = 1,2, \dots , N, t = 1,2, \dots , T$$

Model in which all parameters vary according to units but are constant over time:

$$Y_{it} = \beta_{0i} + \sum_{i=1}^{K} \beta_{ki} X_{kit} + \mu_{it} \ , i = 1,2, \dots , N, t = 1,2, \dots , T$$

Model in which all parameters vary both by unit and time:

$$Y_{it} = \beta_{0i} + \sum_{i=1}^{K} \beta_{kit} X_{kit} + \mu_{it} \ , \ i = 1,2,\dots,N, \ t = 1,2,\dots,T$$

3.1.1.1. Ordinary Least Squares (OLS) Method

The Ordinary Least Squares (OLS) method is a fundamental statistical technique used to estimate the relationships between variables in a linear regression model. It minimizes the sum of the squared differences between the observed and predicted values, thereby providing the best linear unbiased estimators of the coefficients. OLS is widely used due to its simplicity and efficiency, especially when the underlying assumptions of the model are met, such as linearity, independence, and homoscedasticity of errors (Fabozzi & Francis, 1978).

3.1.1.2. Fixed Effects Model

The Fixed Effects Model is a powerful tool in panel data analysis that accounts for unobserved heterogeneity by allowing for individual-specific intercepts. This model assumes that individual characteristics that do not vary over time can impact the dependent variable, and it controls for these effects by differencing them out. By focusing on within-unit variations over time, the Fixed Effects Model provides consistent estimates even in the presence of time-invariant omitted variables, making it particularly useful for studying changes within entities (Nguyen et al., 2020).

3.1.1.3. Random Effects Model

The Random Effects Model, another essential approach in panel data analysis, assumes that the individual-specific effects are randomly distributed and uncorrelated with the independent variables (Faiteh & Aasri, 2022). This model considers both within-unit and between-unit variations, offering more efficient estimations than the Fixed Effects Model when the assumption of no correlation holds. The Random Effects Model is suitable when the individual effects are thought to be randomly drawn from a larger population, allowing for inferences that extend beyond the sampled entities.

3.1.2. Tests for Defining the Model

Classical linear regression models analyze the linear relationship between variables and are interested in how much of the dependent variable is explained by the independent variables. However, panel data models take into account the unit dimension as well as the time dimension. When interpreting the effects of the independent variable on the dependent variable, the value of the coefficient in both the unit and time dimensions is taken into account. While classification is made in panel data according to both unit and time or only unit or only time, no such distinction is made in classical linear regression models. After estimating the panel data models, it is necessary to decide which model will be the most appropriate model. For this, a number of tests are performed. Before applying these tests, the data structure must be taken into consideration. If the data does not come from a large population, there is a clustering on the sample units and these units have the same characteristics, then it can be said that the fixed effects model is appropriate. In the fixed effects model, each unit effect is taken into account. If the data is selected from a large population and the units reflect different characteristics due to its effect, then choosing the random effects model will provide more accurate results (Verbeek, 2017). The decision on which model to choose is also made by looking at the size of the unit and time dimension. It is possible to make some inferences on this issue. If the fixed effects model is chosen when the unit dimension is larger than the time dimension, it will be more appropriate to choose the random effects model since the degree of freedom problem will be encountered (Güriş, 2015). The most commonly used tests for this purpose are the F test, the Breusch–Pagan Lagrange multiplier test and the Hausman test.

3.1.2.1. F Test

This test is used to determine whether unit effects are present in the model. The purpose of the test is to test the presence of unit and/or time effects. Since the null hypothesis states that there are no unit effects, when the null hypothesis cannot be rejected, the classical model should be used. In the suitability of the classical model, parameter estimates are made with the Pooled Ordinary Least Square (POLS) method. When applying the F test, two models are created, restricted and unrestricted. While the restricted model assumes that the differences between the units are not significant, the unrestricted model is assumed to vary according to the units (Ayrıçay & Türk, 2014). This test can be considered as an adaptation of the Chow test in structural terms. The F test is based on the difference of the residual sum of squares of the restricted and unrestricted models. The restricted model is estimated by the least squares method and the residual sum of squares is shown as SSR_R. The unrestricted model is considered as a model where the parameters vary according to units and the residual sum of squares of this model is shown as SSR_{UR}.

The unrestricted model is shown as:

$$Y_i = \alpha_i + X_i\beta_i + u_i$$

and the restricted model:

$Y_i = X_i\beta_i + u_i$

Hypotheses to be tested:

$H_0: \alpha_i = 0$, $i = 1,2,\ldots,N$ (There is no unit effect, the classical model is valid)

$H_1: \alpha_i \neq 0$, $\exists i$ (There is a unit effect, the fixed effects model is valid)

The relevant test statistic is expressed as follows:

$$F = \frac{SSR_R - SSR_{UR}}{SSR_{UR}} \frac{NT - (K-1)}{q}$$

q is the number of constraints. The test statistic given in the equation fits the F distribution with q and $NT - (K - 1)$ degrees of freedom. This test is a one-sided test and if the calculated value exceeds the critical point in the right tail, the H_0 hypothesis is rejected and it is decided that the classical model is not suitable. In this case, the fixed effects model should be used. Otherwise, since the unit effects are not found to be significant, the classical model is valid and POLS can be used (Ang & Chen, 2007).

3.1.2.2. Breusch – Pagan Lagrange Multiplier Test

The Breusch-Pagan Lagrange Multiplier (LM) test is a statistical test used to find the presence of random effects in panel data models. This test is specifically useful in determining whether a pooled ordinary least squares (OLS) model is appropriate or if a random effects model should be used (Alnori et al., 2021). The test is rely on the null hypothesis that there are no random effects, which indicates that the residuals from the model are homoscedastic and independent across cross-sections. If the null hypothesis is rejected, it suggests that a random effects model is more appropriate due to the presence of unobserved heterogeneity among the entities in the panel data.

The formula of LM test is shown as below:

$$LM = \frac{NT}{2(T-1)} \left[\frac{\sum_{i=1}^{N} (\sum_{i=1}^{T} u_{i,t})^2}{\sum_{i=1}^{N} \sum_{i=1}^{T} u^2{}_{i,t}} - 1 \right] \left[\frac{\sum_{i=1}^{N} (\sum_{i=1}^{T} u_{i,t})^2}{\sum_{i=1}^{N} \sum_{i=1}^{T} u^2{}_{i,t}} - 1 \right]$$

Hypothesis to be tested is shown as follows:

H_0: $\sigma_a^2 = 0$ (Since the variance of unit effects is equal to zero, there is no unit effect. The classical model is valid).

H_1: $\sigma_a^2 > 0$ (Since the variance of unit effects is not equal to zero, there is a unit effect. The random effects model is valid).

3.1.2.3. Hausman Test

The Hausman test is an important statistical test used in panel data analysis. This test is used to compare the consistency of the estimates of fixed effects and random effects models when choosing between these two models. The main purpose of the Hausman test is to question the validity of the assumptions of the random effects model. If the random effects model is less consistent than the fixed effects model, it is concluded that the fixed effects model should be preferred (Gallo, 2023). The Hausman test plays a critical role in distinguishing the effects of individual effects and time-varying factors in panel data sets. In addition, this test examines the relationship between the error terms in the model and the independent variables (Ketokivi et al., 2021).
Hypothesis to be tested is shown as follows:

h_0: E($a_i x_{i,t}$) = 0 (Unobserved effects and dependent variables are irrevelant, random effects model is appropriate.)
h_1: E($a_i x_{i,t}$) ≠ 0 (Unobserved effects and dependent variables are revelant, fixed effects model is appropriate.)

3.1.2.4. Autocorrelation Test

The Durbin-Watson (DW) test statistic is a widely used diagnostic tool in econometrics and statistics, particularly for detecting autocorrelation in the residuals of regression models, including fixed effects models in panel data analysis. The DW statistic is calculated as follows:

$$DW = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2}$$

where e_t represents the residuals from the regression model at time t. The value of the DW statistic ranges from 0 to 4, with a value around 2 indicating no autocorrelation. Values significantly less than 2 suggest positive autocorrelation, while values significantly greater than 2 indicate negative autocorrelation (Proïa, 2013). In the context of fixed effect models, the DW test is particularly important because these models account for unobserved heterogeneity by controlling for unit-specific effects. However, the application of the DW test in fixed effect settings can be complicated by the transformation of the data that occurs when estimating the model. For example, the fixed effect transformation can change the distribution of the residuals and potentially affect the performance of the DW test (Born & Breitung, 2016).

3.2.Cluster Analysis Methods

Cluster analysis is a method that allows the units examined in a study to be classified into certain groups according to their similarities, to reveal the common characteristics of the units, and to make general definitions about these classes (Çelik, 2013). The overall objective of cluster analysis is to classify ungrouped data in similarity terms. This analysis method would also be beneficial in deriving appropriate representative information useful.

3.2.1. Hierarchical Clustering Methods

Cluster analysis is basically performed in two different ways. The first of these is hierarchical cluster analysis. This method is the most frequently used method in practice (Tekin, 2018). Hierarchical clustering methods are divided into two as agglomerative and divisive hierarchical. The most preferred of these two is the agglomerative hierarchical method because it is easy to read and interpret. In this method, the observations obtained at the first stage are collected in a cluster and then the observations that are most contrary to this cluster are removed from the cluster and other clusters are formed. In this method, the number of clusters is determined based on the researcher's prior knowledge and experience. Then, clusters are formed by creating similar observations around a certain observation of each cluster (Tekin, 2018).

3.2.1.1. Ward Technique

In the Ward technique, the total deviation squares are used based on the average distance of the observation falling in the middle of a cluster from the observations in the same cluster (Sharma and Wadhawan, 2009).

The formula of Ward technique is shown below:

$$ESS = \sum_{i=1}^{n} x_i^2 - \frac{(\sum_{i=1}^{n} x_i^2)}{n}$$

At the formula,

- x_i is the score of the i'th observation and
- n is the number of data (Aldenderfer and Blashfield, 1984).

3.2.2. Non-Hierarchical Clustering Methods

In non-hierarchical clustering techniques, there is prior knowledge about the number of clusters or the researcher decides on a meaningful number of clusters. Non-hierarchical techniques are applied to larger data sets than hierarchical techniques. Non-hierarchical techniques start with an initial set of core points, which are either the initial parts of the units in the groups or the cores of the clusters. One way to start is to randomly select the core points among the units or to randomly split the units in the initial groups (Johnson and Wichern, 1992).

3.2.2.1. K-Means Technique

In this method, the number of clusters is determined to be at least 2 and equal to or less than the maximum number of observations. The purpose of the k-means method is to classify observations into clusters, the number of which is determined by the researcher. As a result, observations are placed in different clusters with the k-means method algorithms in such a way that the variability between clusters is the largest and the variability within clusters is the smallest (Johnson and Wichern, 1992).

CHAPTER IV

FINDINGS ON FUNDAMENTAL BETA AND FIRM-SPECIFIC VARIABLES: IMPLEMENTATION FOR DEVELOPED MARKETS

This section includes information about the sample used in the study, data and methodology section, research hypothesis and findings of this study. The variables used in the study are also explained in this section.

4.1. Research Sample and Period

In this study, data of companies operating in the industrial sector in 18 developed countries by the Morgan Stanley Capital International (MSCI) will be used. Within the framework of fundamental beta calculations, log of dividend per share, quick ratio, liabilities to assets ratio, log of earnings before interest and taxes, log of total assets, asset turnover and return on asset data will be used, as well as beta of stock prices of companies.

In the study, annual data for a total of 418 companies from 18 countries (Australia, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, United Kingdom and United States) between 2016 and 2023 is used. The study includes a total of 3344 observations. To observe the panel data, Eviews 13.0 and Stata 15 statistic programmes are used. Also for the cluster analysis, SPSS 24.0 package programme is used.

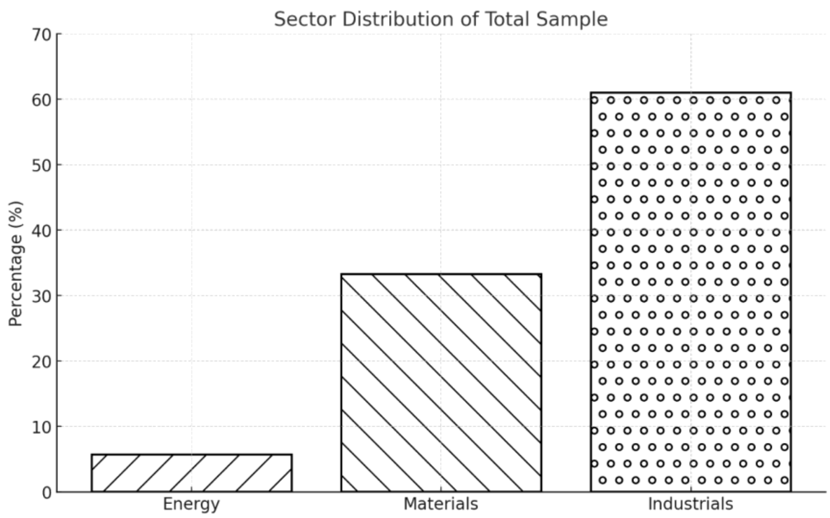

Figure 2. Sector Distribution of Total Sample

The sector distribution of the total sample is predominantly composed of Industrials, accounting for 61.0% of the sample. This is followed by Materials, which represent 33.3%, and Energy, making up the remaining 5.7%.

Table 2.

Sectoral Distribution of Total Sample

	Sectoral Distribution			
Countries	Energy	Industrials	Materials	TOTAL
Australia	4	14	16	34
Canada	4	4	5	13
Denmark			1	1
France		1		1
Germany	2	19	10	31
Hong Kong		1		1
Ireland; Republic of			1	1
Italy	1	3	1	5
Japan	1	93	43	137
Netherlands		2	3	5
New Zealand		4		4
Norway	1		1	2
Singapore		3		3
Spain		2	1	3
Sweden		16	4	20
Switzerland		16	4	20
United Kingdom	1	17	14	32
United States of America	10	60	35	105
TOTAL	24	255	139	418

Table 2 examines the sectoral distribution of industries across different countries within the *Energy*, *Industrials,* and *Materials* categories. The total representation amounts to 418, with the *Industrials* sector accounting for the largest share (255), followed by *Materials* (139) and *Energy* (24). Japan exhibits the highest sectoral presence with 137 entries, predominantly in *Industrials* (93) and *Materials* (43). This is followed by the United States with 105 entries, Australia with 34, and the United Kingdom with 32. Germany (31), Sweden (20), and Switzerland (20) also contribute significantly. Countries with more limited representation include Canada (13), Italy (5), and France (1). The distribution highlights the varying sectoral intensities across countries, emphasizing the dominant global presence of the *Industrials* sector.

4.2. Data and Methodology

The general purpose of this research is to measure the sensitivity of the companies operating in the industrial sector of developed countries to the market with the fundamental beta CAPM method.

The hypotheses of the research are as follows:

$\boldsymbol{H_0}$**:** In developed country markets, firm-specific variables have no effect on systematic risk.

$\boldsymbol{H_1}$**:** In developed country markets, firm-specific variables have an effect on systematic risk.

In this study, the stock data of companies operating in the industrial sector of 18 countries selected from the developed countries category will be used as variables.

In the model put forward by William Sharpe (1964), the relationship between a dominant factor thought to be effective on a financial asset and the returns of that asset is observed. As a definition, the word systematic risk was used for the first time in this model.

According to the CAPM model, the return of a stock should be at least as much as the return of treasury bills, which is known as the riskless asset type. Above this return level, the expected return based on the stock's beta value and the expected market return should be determined. The return on an asset according to CAPM is calculated according to the following formula:

$$R_i = R_f + \beta_i(R_m - R_f)$$

R_i= return on stock

R_f= return on risk-free asset (return of treasury bill)

β_i = Beta coefficient (sensivity of the stock prices to the market variable)

R_m= return on market variable

Regarding the examination of fundamental beta, the variables in Beaver and others' study (1970) were intended to be evaluated as variables in this study. The following method have been used in these mentioned work:

$$\beta_i = a_0 + a_1 X_1 + a_2 X_2 + \ldots . a_N X_N + e_i$$

X_i , shows each variables that affects the beta.

1) Dividend distribution

2) Growth in assets

3) Leverage (Debt/Asset)

4) Liquidity (Current ratio)

5) Volatility in earnings (standard deviation of earnings/price ratio)

6) Total Assets

7) Accounting beta (shows the relationship between firm earnings and average economic earnings).

Market beta will be calculated as below:

$$\beta_i = \frac{Cov_{i,m}}{\sigma_m^2} = \frac{\sum_{t=1}^{n}\left[\left(R_{it} - \overline{R_{it}}\right)\left(R_{mt} - \overline{R_{mt}}\right)\right]}{\frac{\sum_{i=1}^{n}\left(R_{mt} - \overline{R_{mt}}\right)^2}{n}}$$

In the research methodology, the coefficients of the model will be tried to be estimated with the multiple regression method. The period of the research was determined as between 2016-2023, due to lack variables of beta coefficient.

In this dissertation, dependent variable is defined as market beta (BETA). All other variables are independent and defined as dividend per share (DPS), quick ratio (QR) as liquidity indicator, total assets (TA) as firm size, return on assets (ROA) and earnings before interest and taxes (EBIT) as profitability indicator, liabilities to assets (LTA) as financial leverage and asset turnover (AT) as efficiency.

So, the regression model is determined in this dissertation as follows:

$$Beta_{i,t} = \alpha_0 + \beta_1 logdps_{i,t} + \beta_2 qr_{i,t} + \beta_3 roa_{i,t} + \beta_4 logebit_{i,t} + \beta_5 lta_{i,t} + \beta_6 at_{i,t} + \beta_7 logta_{i,t} + \varepsilon_{i,t}$$

All other variables used in this dissertation are explained at the Table 3.

Table 3.

Definitions of Variables Used in the Research

Abbreviation	Variable Name	Description
logdps	Dividend per share (DPS)	is the sum of declared dividends issued by a company for every common stocks outstanding. Logarithm of dividend values have used.
qr	Quick Ratio (QR)	is the total amount of cash, cash equivalents and marketable securities divided by current liabilities.
roa	Return on assets (ROA)	is calculated by dividing a company's net income by its total assets
logebit	Earnings before interest and tax (EBIT)	is the sum of total revenue minus cost of goods sold minus operating expenses. Logarithm of ebit values have used.
lta	Liabilities to assets (LTA)	is the ratio of total liabilities to total assets.
at	Asset turnover (AT)	is a ratio found by net sales divided by average total assets.
logta	Total assets (TA)	is total amount of assets. Logarithm of total asset amounts have used.

Source: investopedia.com. Prepared by author.

4.3. Findings

In the findings section, the sample used in the study will first be grouped using cluster analysis. Then, the slope coefficients of these clusters will be examined through the Wald test. Following the assessment of the effects of the slope coefficients, the panel data estimation results will be interpreted in light of the potential differences among the clusters identified via the clustering procedure. Additionally, the dataset will be examined through descriptive statistics, unit root tests, and cross-sectional dependence tests.

4.3.1. Cluster Analysis Results

In this study, cluster analysis was used to observe differences based on countries and variables. The findings will be explained separately under each heading. This cluster calculations have used for defining clusters for sample used in this research. With the help of this definition, Wald test have used to examine whether there is a difference in groups in the context of independent variables' effect on dependent variable.

4.3.1.1. Final Cluster Centers

Final cluster centers were determined for three clusters:

Table 4.

Final Cluster Centers

	Clusters		
	1	2	3
logdps	-,392048	-,039498	-,089333
qr	2,502619	1,031091	27,260333
roa	,101595	,075976	,077333
logebit	8,264226	8,903867	8,082333
logta	9,322036	10,005692	9,239333
lta	,351464	,591399	,058000
at	,891869	,922610	,456333

The following findings can be stated regarding the final cluster centers shown in Table 10:

- Cluster 1: Generally shows medium values. Although qr (current ratio) is particularly high, logebit and logta values are found to be relatively low.
- Cluster 2: logebit and logta values are found to be the highest values. The qr value is at a medium level. It can be interpreted that it is a financially balanced group.
- Cluster 3: The qr value is quite high (27.26), which may indicate that companies with excessive liquidity are concentrated in this cluster. However, lta (total return on assets) is at the lowest level.

4.3.1.2.ANOVA Test Results

Table 5.

ANOVA Test Results

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
logdps	4,164	2	,312	415	13,346	,000
qr	1073,955	2	,468	415	2293,339	,000
roa	,022	2	,003	415	7,642	,001
logebit	14,419	2	,376	415	38,312	,000
logta	16,244	2	,279	415	58,154	,000
lta	2,279	2	,021	415	106,819	,000
at	,347	2	,260	415	1,336	,264

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

ANOVA results show the significance level of differences between the clusters on the variables. The test results were interpreted as follows:

- There are significant differences between the clusters among the variables logdps, qr, roa, logebit, logta, and lta ($p < 0.05$).
- The variable at (asset turnover rate) did not show significant differences between the clusters ($p > 0.05$). This shows that the active turnover rate between the clusters is similar.

4.3.1.3. Cluster Sizes

The distribution of clusters is as follows:

- Cluster 1: 84 observations
- Cluster 2: 331 observations (the vast majority)
- Cluster 3: 3 observations

Cluster 3 contains countries with extreme outliers (the anomaly in the qr value supports this). Cluster 2 represents countries with large economies, while Cluster 1 may represent economies that are more financially moderate.

4.3.1.4.Cluster Distribution By Country

Table 6.

Cluster Sizes by Countres

Country	Cluster 1	Cluster 2	Cluster 3	Total
Australia	9	25	0	34
Canada	0	11	2	13
Denmark	0	1	0	1
France	0	1	0	1
Germany	7	24	0	31
Hong Kong	0	1	0	1
Ireland; Republic of	0	1	0	1
Italy	0	5	0	5
Japan	50	86	1	137
Netherlands	0	5	0	5
New Zealand	1	3	0	4
Norway	0	2	0	2
Singapore	2	1	0	3
Spain	0	3	0	3
Sweden	0	20	0	20
Switzerland	2	18	0	20
United Kingdom	7	25	0	32
United States of America	6	99	0	105

All results by clusters are explained as below:

Cluster 1:

- Countries such as Australia, Germany and Japan are quite prominent in Cluster 1, with Japan (50 observations) being the country with the most presence in this cluster.
- The United Kingdom (7) and the United States (6) are also prominent in Cluster 1, and stand out as important representatives in this cluster.

- Countries such as Canada, Denmark, France and Hong Kong are almost completely absent from Cluster 1, indicating that their economies and sectoral structures do not fit into this cluster.

Cluster 2:

- Cluster 2 is heavily represented by large developed economies such as Japan (86 observations), the United States (99 observations), and the United Kingdom (25 observations). These countries represent Cluster 2 with their large, industrialized, and diversified economies.
- Countries such as Switzerland (18), Germany (24), and Australia (25) also feature prominently in Cluster 2.

Cluster 3:

- Cluster 3 is very underrepresented. It contains almost no countries except Japan (1 observation) and Canada (2 observations). Cluster 3 may represent countries with very different economic structures from the other clusters, and therefore very few countries are included in this cluster.
- Countries such as Denmark, Ireland, and France are barely represented in Cluster 2, suggesting that these countries have different sectoral focuses or economic structures.

4.3.1.5.Countries and Clustering Results

The total observations by country graph is given below:

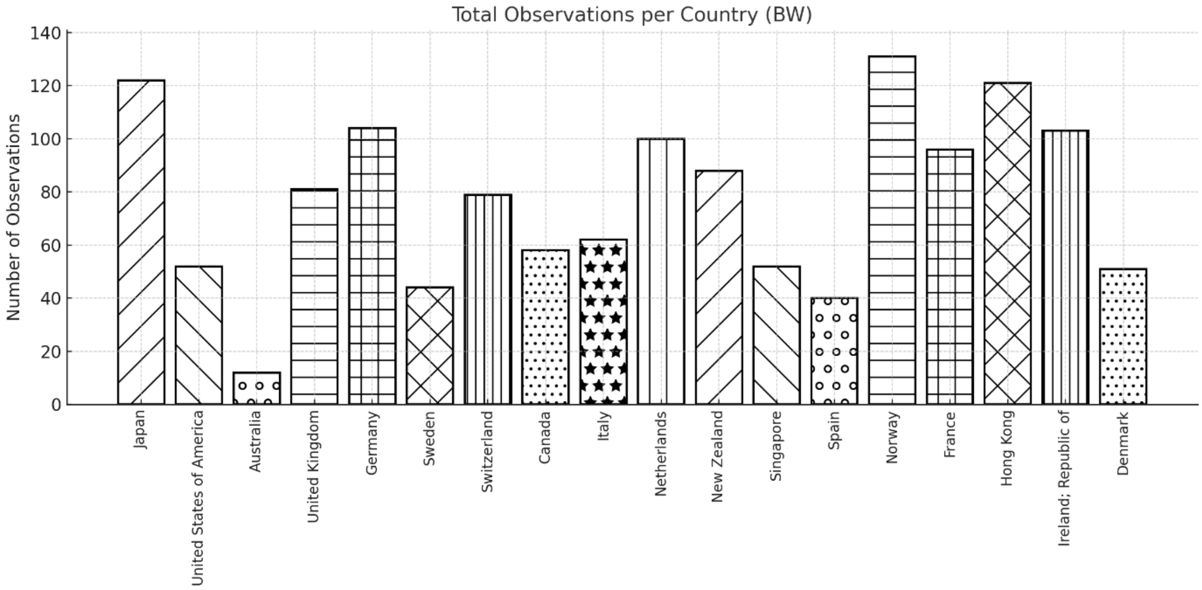

Figure 3. Total Observations per Country

The findings are interpreted as follows:

- Japan: The country with the most data with 137 observations.
- The United States: Second with 105 observations.
- Australia, the United Kingdom and Germany: Stand out with 34, 32 and 31 observations, respectively.

4.3.1.6. Cluster Distribution by Country

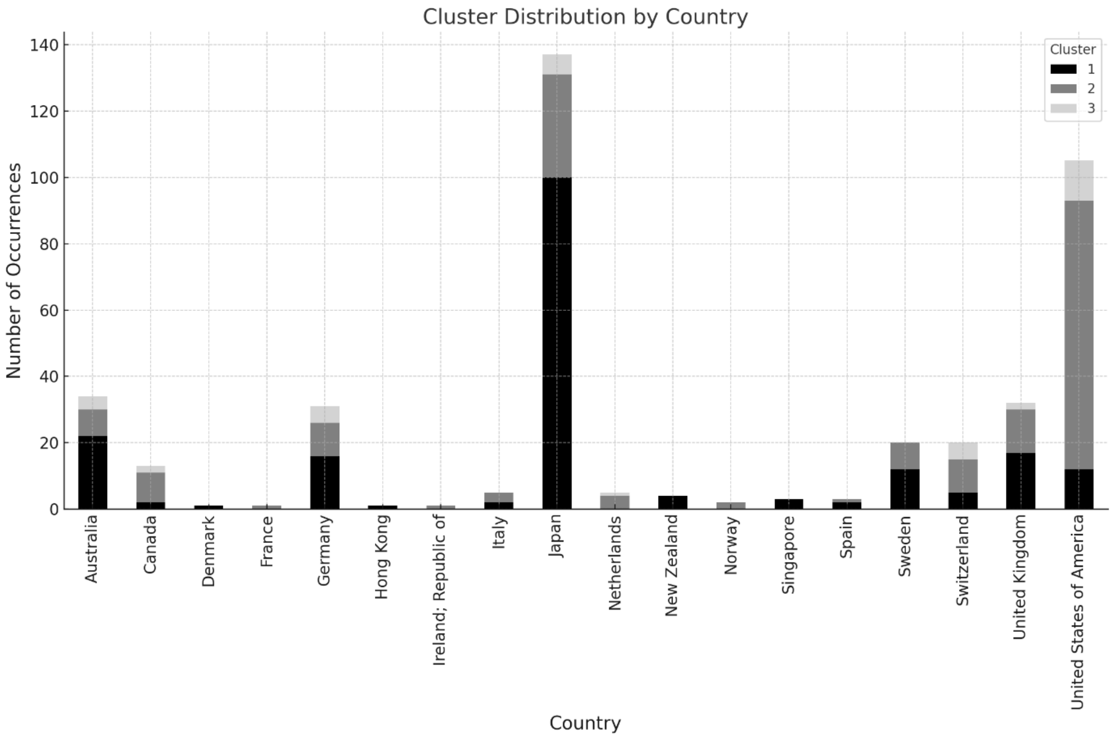

Figure 4. Cluster Distribution by Country

The findings are interpreted as follows:

- Countries like the United States, United Kingdom, Germany, and Japan are prominently in Cluster 1. This suggests that these countries may have similar economic structures or industrial sectors, making them part of the same cluster.
- Cluster 2 and Cluster 3 represent fewer countries, with most countries in Cluster 1. However, countries like Japan, United Kingdom, and Germany appear in Cluster 2, suggesting that they have features that also place them in this cluster in addition to Cluster 1.
- Cluster 3 has the fewest countries, which could indicate that the countries in this cluster have unique or specific characteristics. Japan and the United States are also present in Cluster 3, indicating that these countries might have complex or diverse features that set them apart from other countries.
- The concentration of countries in Cluster 1 suggests that these countries might have similar industrial bases, economic development levels, or trade

relationships. For example, the United States, United Kingdom, and Germany are highly industrialized, developed economies with global influence, which may explain their similar clustering.

After the classification of groups through cluster analysis, the Wald test will be employed to investigate the group-specific slope coefficients of the independent variables.

4.3.2. Wald Test Results

Following the previous section, the firm-level dependent and independent variables were averaged across the years, generating a single cross-sectional value for each variable per firm. Based on this dataset, cluster analysis was conducted. The study then tested, through the Wald test, whether the impact of each independent variable on systematic risk varied significantly across the three identified clusters. The results were reported independently for each explanatory variable.

Table 7.

Wald Test Results (logdps)

Test	F-Value	Prob > F	Result
H_0: $\beta_0 = \beta_1 = \beta_3 = 0$	9.83	0.0000	Reject
H_0: $\beta_0 = \beta_1 = \beta_3$	9.31	0.0001	Reject
H_0: $\beta_0 = 0$	23.97	0.0000	Reject
H_0: $\beta_1 = 0$	0.10	0.7489	Accept
H_0: $\beta_3 = 0$	12.05	0.0005	Reject

Here, β_0 denotes the slope coefficient vector of reference cluster (cluster 2). β_1 denotes the slope coefficient vector of *logdps* for Cluster 1, while β_3 represents the slope coefficient vector of *logdps* for Cluster 3.

The first independent variable examined was the logarithmic value of dividend per share (logdps). According to the first null hypothesis of the Wald test (H_0: $\beta_0 = \beta_1 = \beta_3 = 0$), this variable does not affect the dependent variable, systematic risk (beta), in any of the clusters—meaning all coefficients are equal and equal to zero. The result of the Wald test rejects the null hypothesis ($F = 9.83$, $p = 0.0000 < 0.01$), indicating that the logdps coefficient has a significant effect on systematic risk (i.e., the coefficients are not equal to zero), and that the slope coefficients differ in at least one cluster.

The second null hypothesis (H_0: $\beta_0 = \beta_1 = \beta_3$), which assumes that the effect of the independent variable on systematic risk is equal across all clusters, is also rejected (F = 9.31, p = 0.0001). This suggests that the impact of the independent variable on systematic risk significantly differs across at least one group.

The third null hypothesis (H_0: $\beta_0=0$) tests whether the coefficient of the independent variable in the second cluster (the reference group) is equal to zero. The Wald test result rejects this hypothesis as well (F = 23.97, p = 0.0000), indicating that the coefficient in the reference cluster is significantly different from zero and that the independent variable has an effect on the dependent variable.

The fourth null hypothesis (H_0: $\beta_1=0$) posits that the slope coefficient of the independent variable in the first cluster is equal to zero. The result fails to reject the null hypothesis, suggesting that the slope coefficient of the independent variable in the first cluster is not significantly different from that of the reference group.

Finally, the fifth null hypothesis (H_0: $\beta_3=0$), which tests whether the slope coefficient of the independent variable in the third cluster is equal to zero, is rejected (F = 12.05, p = 0.0005). This indicates that the slope coefficient in the third cluster differs significantly from that of the reference group. If the slope coefficient from the panel fixed effects model is statistically significant, the coefficient for the third cluster should be calculated by summing the reference group's slope coefficient and the slope coefficient of the third cluster.

Table 8.

Wald Test Results (qr)

Test	**F-Value**	**Prob > F**	**Result**
H_0: $\beta_0 = \beta_1 = \beta_3 = 0$	7.85	0.0000	Reject
H_0: $\beta_0 = \beta_1 = \beta_3$	3.12	0.0444	Reject
H_0: $\beta_0=0$	1.88	0.1703	Accept
H_0: $\beta_1=0$	0.46	0.4979	Accept
H_0: $\beta_3=0$	2.39	0.1221	Accept

Here, β_0 denotes the slope coefficient vector of reference cluster (cluster 2). β_1 denotes the slope coefficient vector of *qr* for Cluster 1, while β_3 represents the slope coefficient vector of *qr* for Cluster 3.

The next independent variable examined was the quick ratio (qr). The null hypothesis suggesting that this variable has no effect on systematic risk was rejected (F = 7.85, p = 0.0000). This result indicates that the qr coefficient significantly influences systematic risk (i.e., the slope coefficients are not equal to zero), and that the slope coefficients differ in at least one cluster.

The second null hypothesis, which posits that the qr coefficient does not vary across clusters, was also rejected at the 0.05 significance level (F = 3.12, p = 0.0444). This suggests that the effect of the independent variable differs across at least one group.

The third null hypothesis, which tests whether the coefficient of the independent variable in the reference cluster is equal to zero, could not be rejected (F = 1.88, p = 0.1703). This implies that the qr variable does not have a significant effect on systematic risk in the reference cluster.

Similarly, the fourth and fifth null hypotheses — which test whether the qr variable has no effect on systematic risk in the first and third clusters, respectively — were also not rejected (F = 0.46, p = 0.4979 for the fourth hypothesis, and F = 2.39, p = 0.1221 for the fifth). These findings indicate that the quick ratio does not have a statistically significant effect on systematic risk in either the first or third clusters.

Table 9.

Wald Test Results (roa)

Test	**F-Value**	**Prob > F**	**Result**
H_0: $\beta_0 = \beta_1 = \beta_3 = 0$	12.62	0.0000	Reject
H_0: $\beta_0 = \beta_1 = \beta_3$	1.25	0.2877	Accept
H_0: $\beta_0 = 0$	15.63	0.0001	Reject
H_0: $\beta_1 = 0$	0.07	0.7961	Accept
H_0: $\beta_3 = 0$	9.68	0.0019	Reject

Here, β_0 denotes the slope coefficient vector of reference cluster (cluster 2). β_1 denotes the slope coefficient vector of *roa* for Cluster 1, while β_3 represents the slope coefficient vector of *roa* for Cluster 3.

Next, the slope coefficients of the return on assets (roa) variable were examined. The null hypothesis stating that this independent variable does not affect systematic risk was rejected (F = 12.62, p = 0.0000). This indicates that the roa coefficient significantly influences systematic risk (i.e., the slope coefficients are not equal to zero), and that the slope coefficients differ in at least one cluster.

The second null hypothesis, which posits that the slope coefficients of the independent variable do not vary across clusters, could not be rejected (F = 1.25, p = 0.2877), suggesting that the effect of roa does not significantly differ across groups.

The third null hypothesis, which tests whether the coefficient of the independent variable in the reference cluster is equal to zero, was rejected (F = 15.63, p = 0.0001). This indicates that the independent variable significantly affects systematic risk within the reference cluster.

The fourth hypothesis, which suggests that the slope coefficient of the independent variable in the first cluster is equal to zero, could not be rejected (F = 0.07, p = 0.7961). This implies that the slope coefficient of the independent variable in the first cluster is statistically equal to that of the reference cluster.

Finally, the fifth null hypothesis, which tests whether the slope coefficient of the independent variable in the third cluster is equal to zero, was rejected (F = 9.68, p = 0.0019). This indicates that the slope coefficient in the third cluster is significantly different from that of the reference cluster.

Table 10.

Wald Test Results (logebit)

Test	F-Value	Prob > F	Result
H_0: $\beta_0 = \beta_1 = \beta_3 = 0$	1.26	0.2871	Accept
H_0: $\beta_0 = \beta_1 = \beta_3$	0.96	0.3836	Accept
H_0: $\beta_0 = 0$	3.43	0.0641	Accept
H_0: $\beta_1 = 0$	0.12	0.7285	Accept
H_0: $\beta_3 = 0$	0.95	0.3292	Accept

Here, β_0 denotes the slope coefficient vector of reference cluster (cluster 2). β_1 denotes the slope coefficient vector of *logebit* for Cluster 1, while β_3 represents the slope coefficient vector of *logebit* for Cluster 3.

The subsequent independent variable examined was the logarithmic value of earnings before interest and taxes (logebit). The Wald test failed to reject the null hypothesis that all slope coefficients are equal to zero (F = 1.26, p = 0.2871), indicating that logebit does not have a statistically significant effect on systematic risk in any of the clusters. As the remaining null hypotheses were also not rejected, no further interpretation regarding cluster-specific effects was deemed necessary.

Table 11.

Wald Test Results (logta)

Test	F-Value	Prob > F	Result
$H_0: \beta_0 = \beta_1 = \beta_3 = 0$	12.26	0.0000	Reject
$H_0: \beta_0 = \beta_1 = \beta_3$	7.73	0.0004	Reject
$H_0: \beta_0 = 0$	34.36	0.0000	Reject
$H_0: \beta_1 = 0$	0.38	0.5372	Accept
$H_0: \beta_3 = 0$	7.89	0.0050	Reject

Here, β_0 denotes the slope coefficient vector of reference cluster (cluster 2). β_1 denotes the slope coefficient vector of *logta* for Cluster 1, while β_3 represents the slope coefficient vector of *logta* for Cluster 3.

The next independent variable examined was the logarithmic value of total assets (logta). The first null hypothesis, which assumes that all slope coefficients are equal to zero, was rejected (F = 12.26, p = 0.0000). This indicates that the slope coefficient of logta is significantly different from zero and that the effect of this variable on systematic risk varies in at least one cluster.

The second null hypothesis, which posits that all slope coefficients are equal across clusters, was also rejected (F = 7.73, p = 0.0004), suggesting that the effect of logta on systematic risk significantly differs across the identified clusters.

The third null hypothesis, which tests whether the slope coefficient in the reference group is equal to zero, was rejected as well (F = 34.36, p = 0.0000). This implies that logta has a statistically significant effect on systematic risk within the reference cluster.

The fourth null hypothesis, assuming that the slope coefficient of the independent variable in the first cluster is equal to zero, could not be rejected (F = 0.38, p = 0.5372). This result suggests that the coefficient in the first cluster does not significantly differ from that of the reference group.

Finally, the fifth null hypothesis, which posits that the slope coefficient in the third cluster is equal to zero, was rejected (F = 7.89, p = 0.0050), indicating that the effect of logta in the third cluster significantly differs from the reference group.

Table 12.

Wald Test Results (lta)

Test	**F-Value**	**Prob > F**	**Result**
H_0: $\beta_0 = \beta_1 = \beta_3 = 0$	7.16	0.0001	Reject
H_0: $\beta_0 = \beta_1 = \beta_3$	1.14	0.3197	Accept
H_0: $\beta_0 = 0$	12.11	0.0005	Reject
H_0: $\beta_1 = 0$	0.28	0.5957	Accept
H_0: $\beta_3 = 0$	5.01	0.0252	Reject

Here, β_0 denotes the slope coefficient vector of reference cluster (cluster 2). β_1 denotes the slope coefficient vector of *lta* for Cluster 1, while β_3 represents the slope coefficient vector of *lta* for Cluster 3.

The next independent variable analyzed is the liabilities-to-assets ratio (lta). The first null hypothesis, which assumes that all slope coefficients are equal to zero, was rejected. This indicates that the independent variable has a statistically significant effect on systematic risk in at least one of the clusters.

The second null hypothesis, which posits that the slope coefficients of the independent variable are equal across clusters, could not be rejected ($F = 1.14$, $p = 0.3197$). This suggests that the effect of the variable on systematic risk does not significantly differ between clusters.

Table 13. *Wald Test Results (at)*

Test	**F-Value**	**Prob > F**	**Result**
H_0: $\beta_0 = \beta_1 = \beta_3 = 0$	1.68	0.1685	Accept
H_0: $\beta_0 = \beta_1 = \beta_3$	1.01	0.3638	Accept
H_0: $\beta_0 = 0$	4.58	0.0323	Accept
H_0: $\beta_1 = 0$	0.29	0.5900	Accept
H_0: $\beta_3 = 0$	0.88	0.3496	Accept

Here, β_0 denotes the slope coefficient vector of reference cluster (cluster 2). β_1 denotes the slope coefficient vector of *at* for Cluster 1, while β_3 represents the slope coefficient vector of *at* for Cluster 3.

Finally, the slope coefficients related to the asset turnover (at) variable were examined. None of the null hypotheses were rejected for this independent variable, indicating that the slope coefficients are not significantly different from zero.

After all the explanations, the dataset will be examined through descriptive statistics, unit root tests, cross-sectional dependence tests and panel OLS, random effect model and fixed effect model.

4.3.3. Panel Test Results

4.3.3.1.Descriptive Statistics

Table 14.

Descriptive Statistics

	beta	at	logdps	logebit	qr	logta	lta	roa
Mean	1.094700	0.891013	-0.187372	8.681337	1.494182	9.793301	0.543685	0.073642
Median	1.068745	0.805627	-0.165738	8.646686	1.155410	9.780474	0.555343	0.064300
Maximum	5.011046	4.212134	1.885416	10.87947	31.12867	11.64643	1.253163	0.486590
Minimum	-0.276265	0.044130	-2.777284	6.472071	0.166640	7.937065	0.006247	-0.305300
Std. Dev.	0.439212	0.505717	0.556585	0.612135	1.490772	0.608129	0.178852	0.050791

The sample mean for the dependent variable beta coefficient used in the study was found to be 1.09 and the median was found to be 1.06. Accordingly, it can be said that the stock returns of the companies in the sample countries move parallel to their markets on average. The maximum value of the sample was found to be 5.01 and the minimum value was found to be -0.27. The standard deviation of the beta coefficient is 0.439212.

The sample mean value for asset turnover (at) was found to be 0.89 and the median was found to be 0.80. Accordingly, approximately 89% of the average asset turnover of the companies in the sample is returned as sales revenue. The maximum value of the asset turnover variable was found to be 4.21 and the minimum value was found to be 0.04. The standard deviation of the coefficient is 0.505717.

The sample mean for logdps was found to be -0.018, while the median was -0.16. These findings indicate a decline in dividend payments among firms. The maximum value (1.88) shows that some compaines in the sample have relatively strong dividend payout. The standard deviation of the logdps coefficient is found as 0.556585.

The sample mean and median values for the log(ebit) variable were found to be 8.68 and 8.64. These positive mean and median values reveal that the companies in the sample are generally efficient in terms of operations and show profitability. The maximum value of log(ebit) variable was found to be 10.87 and the minimum value was found to be 6.47. The standard deviation of the log(ebit) coefficient is 0.612135.

The sample mean for the qr variable was found to be 1.49 and the median was found to be 1.15. These positive mean and median values indicate that companies have sufficient liquid assets to cover their liabilities. The maximum value of sample was found 31.12, which indicates that the presence of a companies with a quite strong liquidity. The standard deviation of the qr coefficient is found as 1.490772.

The sample mean for logta was found to be 9.79 and the median was found to be 9.78. The maximum value was 11.64 and the minimum value was 7.93. The standard deviation of the logta coefficient is 0.608129.

The sample mean for lta was found to be 0.54 and the median was found to be 0.55. This result shows that companies in this sample have relatively conservative financial structure with less reliance on debt. The maximum value of sample is 1.25 and the minimum value is 0.006. The standard deviation of the lta coefficient is 0.178852.

The sample mean of roa was found to be 0.07 and the median was found to be 0.06. This finding indicates that firms in this sample are generating a modest return on their assets. The minimum value was found to be -0.30; shows that some companies experiencing losses from their investments on assets. The standard deviation of the roa coefficient is 0.050791.

4.3.3.2. Cross Section Dependency Test

Table 15.

Cross Section Dependency Test Results

	beta	at	logdps	logebit	qr	logta	lta	roa
Breusch-Pagan LM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pesaran Scaled LM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Bias-corrected scaled LM	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pesaran CD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

The null hypothesis is rejected, there is cross-sectional dependence in the series. In this case, it means that a shock or crisis occurring in the variables of the companies included in the analysis affects other variables. Bai and Ng – PANIC test, one of the second-generation unit root tests, will be applied.

4.3.3.3. Panel Unit Root Test Results

Table 16.

Unit Root Test Results

Variables	Value	p-value
beta	-9.75437	0.00000
at	-10.93370	0.00000
logdps	-15.71350	0.00000
logebit	-10.12688	0.00000
qr	-20.04243	0.00000
logta	12.37837	0.00000
lta	-19.76955	0.00000
roa	-19.63598	0.00000

According to the results of the unit root test, since the p values of all variables included in the analysis are less than the critical value of 0.05, the null hypothesis "there is a unit root" is rejected, and it can be concluded that all series do not contain unit roots and the series is stationary.

4.3.3.4.Panel OLS – Fixed Effect – Random Effect Model Testing

The F test result is given at Table 17.

Table 17.

F Test Result

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-0.235334	0.161929	-1.453317	0.1462
at	-0.003398	0.016657	-0.204030	0.8383
logdps	-0.107797	0.015329	-7.032022	0.0000
logebit	0.096498	0.038426	2.511303	0.0121
qr	0.006921	0.005807	1.191939	0.2334
logta	0.053920	0.039886	1.351868	0.1765
lta	-0.005207	0.053782	-0.096807	0.9229
roa	-0.820708	0.225436	-3.640535	0.0003
R-squared			0.051220	
Adjusted R-squared			0.049229	
F-statistic			25.72791	
Prob(F-statistic)			0.000000	
Durbin-Watson stat			0.247032	

The main purpose of the F test is to determine whether it is appropriate to explain the model to be chosen with a least squares or a fixed effects model. If the null hypothesis is rejected as a result of the test, it is concluded that unit effects exist and therefore the fixed effects model is valid. When looking at the table, the F statistic value was found to be 25.72 and the p value of this statistic was found to be 0.00. Accordingly, the existence of a unit effect at a significance level of 5% is valid and the classical model, the pooled least squares model, is not valid. In the current situation, the fixed effects model should be preferred instead of POLS.

4.3.3.5. Random Effect Model Testing

Since the classical model is rejected in both the F test and the Breusch-Pagan LM test, finally the choice will be made between fixed effects and random effects models with the Hausman test. If the test statistic is found to be significant, the fixed effects model will be valid, otherwise the random effects model will be valid. When performing the analyses of the Hausman test, the fixed effects and random effects models must first be estimated.

Table 18.

Hausman Test Result

Test Summary	**Chi-Sq. Statistic**	**Chi-Sq. d.f.**	**Prob.**
Cross-section random	40.898203	7	0.0000

Estimation results and test statistics are given in Table 18. The test statistic is calculated as (X^2=40.89) and the p-value of this statistic is 0.00. Since the p value is less than the critical value of 0.05, the h_0 hypothesis, which suggests that the random effects model is valid, is rejected. Therefore, it was decided to continue the analysis with the fixed effects model.

4.3.3.6.Fixed Effect Model

The fixed effect model test results are given at Table 19.

Table 19.

Fixed Model Statistics

beta	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
logdps	-0.172	0.035	-4.90	0.000	-0.242	-0.103	***
qr	0.022	0.016	1.37	0.17	-0.01	0.055	
roa	-0.839	0.212	-3.95	0.000	-1.255	-0.423	***
logebit	0.068	0.037	1.85	0.064	-0.004	0.14	*
logta	0.391	0.067	5.86	0.000	0.261	0.522	***
lta	0.318	0.091	3.48	0.001	0.139	0.497	***
at	-0.108	0.051	-2.14	0.032	-0.207	-0.009	**
logdps1	0.444	1.387	0.32	0.749	-2.276	3.165	
qr1	-0.015	0.022	-0.68	0.498	-0.058	0.028	
roa1	3.763	14.557	0.26	0.796	-24.78	32.306	
logebit1	-0.833	2.401	-0.35	0.729	-5.541	3.874	
logta1	-1.825	2.957	-0.62	0.537	-7.622	3.973	
lta1	1.748	3.295	0.53	0.596	-4.713	8.21	
at1	0.752	1.396	0.54	0.59	-1.985	3.49	
logdps3	0.499	0.144	3.47	0.001	0.217	0.78	***
qr3	0.031	0.02	1.55	0.122	-0.008	0.07	
roa3	-1.966	0.632	-3.11	0.002	-3.205	-0.727	***
logebit3	-0.132	0.135	-0.98	0.329	-0.396	0.133	
logta3	-0.802	0.286	-2.81	0.005	-1.362	-0.242	***
lta3	1.019	0.455	2.24	0.025	0.127	1.912	**
at3	0.227	0.243	0.94	0.35	-0.249	0.704	
Constant	-2.788	0.609	-4.58	0.000	-3.982	-1.594	***

Mean dependent var	1.095	SD dependent var	0.439
R-squared	0.069	Number of obs	3344
F-test	10.198	Prob > F	0.000
Akaike crit. (AIC)	187.258	Bayesian crit. (BIC)	321.787

**** p<.01, ** p<.05, * p<.1*

All results given at the table above can be described as below:

The R square value was found to be 0.069. This shows that approximately 0.069 of the change in the dependent variable beta coefficient is explained by the independent variables included in the model. The fact that the F statistic is below the critical value shows that the model is significant as a whole.

Logdps (the logarithm value of dividend per share) coefficient was found to be -0,172 and statistically significant at 0,01 level. This result shows that when other variables are constant, an increase in dividend per share leads to a decrease in systematic risk. This finding aligns with the broader literature emphasizing the inverse relationship between dividend payouts and systematic risk. Numerous studies have shown that higher dividend payouts are often associated with lower beta values (Beaver et al., 1970; Breen & Lerner, 1973; Gu & Kim, 2002). The negative coefficient of logdps in the current analysis supports this notion, suggesting that firms distributing higher dividends per share are perceived as less risky by investors. This can be attributed to the signaling effect of dividend policies. When a firm increases its dividends, it often signals financial health, stable cash flows, and management's confidence in future earnings (Biza-Khupe & Themba, 2016). Such signals tend to reduce perceived uncertainty, leading to lower stock price volatility and, consequently, a lower beta. Moreover, investors generally consider dividend income more stable and predictable than capital gains, which further contributes to the negative association between dividend payouts and systematic risk (Logue & Merville, 1972). The result may also reflect the role of dividend policy as a communication tool about a firm's risk profile. Firms with consistent and high dividend payouts are often seen as operating in stable environments or maintaining strong corporate governance structures—factors known to reduce investor-perceived risk (Abor & Fiador, 2013). On the other hand, companies with irregular or low dividend distributions may be viewed as riskier due to potential financial constraints or strategic choices that prioritize uncertain growth opportunities over stable shareholder returns (Sari, 2018).

Roa (return on assets) coefficient was found to be -0,839 and statistically significant at 0,01 level. This result shows that when other variables are constant, an increase in return on assets leads to a decrease in systematic risk. This finding is consistent with the broader financial literature that highlights a negative relationship between profitability and systematic risk. A higher ROA reflects a firm's ability to generate earnings from its assets efficiently, indicating operational strength and financial resilience. Several empirical studies have supported this inverse relationship, showing that more profitable firms often exhibit lower beta values. Notably, research by Borde (1998), Gu and Kim (1998), Logue and Merville (1972), Allozi and Obediat (2016), and

Scherrer & Mathison (1996) emphasizes that firms with higher profitability tend to face less systematic risk. The rationale is that stable and strong returns reduce the firm's vulnerability to external shocks, thereby dampening the volatility of stock returns relative to the market.

The significant negative roa coefficient in this analysis reinforces the view that profitability serves as a stabilizing factor in a firm's risk profile. Firms that manage their assets effectively and consistently generate income are less likely to experience dramatic swings in investor sentiment or market-driven fluctuations. As a result, they are perceived as more stable investments, which translates into a lower beta. In essence, this result supports the theoretical framework in which profitability is not only a measure of performance but also a determinant of how a firm is perceived in terms of market risk. Higher roa levels serve as signals of operational efficiency and long-term sustainability, both of which contribute to a reduction in systematic risk exposure.

Logebit (the logarithm value of earnings before interest and taxes) coefficient was found to be 0,068 and statistically significant at 0,10 level. This result shows that when other variables are constant, an increase in earnings before interest and taxes leads to an increase in systematic risk. This result indicates that as companies' scales become higher and complicated, systematic risk could be higher. This finding aligns with one of the perspectives in the literature that associates business growth—particularly profit-based growth—with increased systematic risk. As measured by earnings before interest and taxes (ebit), growth often signals expansion in a firm's scale, operations, and complexity. While growth is generally viewed positively, it can also introduce additional risk factors, especially when it leads to increased dependence on external financing and greater exposure to market fluctuations. As firms grow, the operational and financial complexities increase, making them more sensitive to external shocks and market dynamics. From this angle, the positive relationship between ebit growth and beta observed in this study may reflect the risks associated with managing growth at scale. This finding has supported by literature (Bowman, 1979; Gu & Kim, 2002; Lee & Jang, 2007; Logue & Merville, 1972).

Logta (the logarithm value of total assets) coefficient was found to be 0,391 and statistically significant at 0,01 level. This result shows that when other variables are constant, an increase in total assets leads to an increase in systematic risk. This finding contributes to the ongoing debate in the financial literature regarding the relationship between firm size—often proxied by total assets—and systematic risk. Traditionally, many studies have supported a negative correlation between company size and beta, suggesting that larger firms benefit from economies of scale, diversified operations, and stronger capacity to absorb shocks, thus exhibiting lower systematic risk (Amato & Amato, 2012; Fisher, 1959). According to this perspective, the larger the firm, the more stable and less sensitive it becomes to market fluctuations. However, the positive and statistically significant coefficient of logta in this study indicates a different dynamic: that an increase in firm size, as measured by total assets, is associated with an increase in systematic risk. This result supports a contrasting line of argument, as seen in the work of Lee and Jang (2007), who found a positive relationship between size and beta in the U.S. airline industry. Their findings suggest that larger firms, particularly those operating in complex or capital-intensive industries, may actually face greater exposure to market risks due to their extensive operations, higher fixed costs, and greater visibility in financial markets. Additionally, Daves et al. (2000) observed a temporal shift in risk dynamics, noting that while smaller firms tended to be riskier prior to 1980, larger firms have exhibited higher beta values in the post-1980 period. This shift has been attributed to changes in capital structures, increased reliance on debt, and larger-scale investments by bigger firms—factors that can elevate financial sensitivity to market changes.

Lta (liabilities-to-assets ratio) coefficient was found to be 0,318 and statistically significant at 0,01 level. This result shows that when other variables are constant, an increase in liabilities to assets leads to an increase in systematic risk. This result aligns with a substantial body of financial literature that links higher leverage with increased systematic risk. The liabilities-to-assets ratio, as a measure of financial leverage, reflects the extent to which a firm relies on debt to finance its assets. When this ratio increases, it typically signals greater financial risk due to the firm's heightened exposure to interest obligations and potential insolvency under adverse market conditions. While Modigliani and Miller (1958) argue that in a perfect capital market, a firm's capital structure does not affect its value or risk, subsequent empirical studies have shown that in real-world conditions—where taxes, bankruptcy costs, and information asymmetries exist—leverage becomes a critical determinant of risk. The literature consistently identifies a positive relationship between financial leverage and beta, indicating that firms with higher debt levels tend to experience greater systematic risk (Borde, 1998; Gu & Kim, 1998; Moyer & Chatfield, 1983).

At (asset turnover) coefficient was found to be -0,108 and statistically significant at 0,05 level. This result shows that when other variables are constant, an increase in asset turnover leads to a decrease in systematic risk. This negative relationship between asset turnover and systematic risk aligns with the argument that firms managing their resources more effectively tend to exhibit lower volatility in earnings and are perceived as less risky by investors. Firms with strong asset management practices are generally subject to lower levels of systematic risk, as they are better equipped to weather market uncertainties and generate consistent returns (Borde, 1998). Moreover, firms with high asset turnover can often recover more quickly from past losses and may require less reliance on external financing, both of which further decrease their exposure to systematic market movements. This interpretation is reinforced by Gu and Gao (2000), who note that although aggressive growth strategies can sometimes inflate profitability, efficiency-oriented strategies tend to promote more sustainable and less volatile performance, ultimately reducing systematic risk.

The findings related to the main sample have been explained in the preceding section. Next, the explanations regarding the three sub-sample groups included in the analysis are presented under the sections discussing the Wald test results and the cluster analysis findings. In this section, only the coefficients found to be statistically significant for the third sub-sample are discussed.

In the main sample, the coefficient of logdps was found to be -0.172 at the 1% significance level. However, in the third cluster (which consists of 3 observations), the logdps coefficient was calculated as 0.327, derived from the sum (-0.172 + 0.499 = 0.327), and this result was also statistically significant at the 1% level. This indicates a shift in the direction of the coefficient's influence on systematic risk: while logdps had a negative impact in the first and second clusters, its effect turned positive in the third cluster.

Similarly, the coefficient of roa in the main sample was identified as -0.839, also significant at the 1% level. In the third cluster, this coefficient dropped to -2.805. This suggests that the negative relationship between roa and systematic risk persists in the third cluster, but the intensity of the effect is notably stronger. The method for determining this coefficient followed the same approach used in the earlier calculation of the logdps coefficient. The same procedure was applied to other coefficients that were found to be statistically significant.

In the main sample, the coefficient of logta was measured at 0.391, again significant at the 1% level, indicating a positive relationship between total assets and systematic risk. However, in the third cluster, the coefficient turned negative, at -0.411, suggesting a reversal in this relationship within that specific group.

Lastly, the lta coefficient in the main sample was recorded as 0.318 at the 1% significance level. In the third cluster, this coefficient increased to 1.337. This implies that changes in the ratio of total debt to assets have a more pronounced impact on systematic risk in the third cluster compared to the overall sample.

Up to this point, the effects of the independent variables in the reference cluster have been interpreted based on the estimation results of the panel fixed effects model. In addition, for the third cluster—where statistically significant effects were also observed as seen in reference cluster—the magnitude of the effects has been discussed by examining the slope coefficients of the relevant independent variables. Although significant differences were detected in four independent variables (logdps, roa, logta, and lta) within the third cluster, it should be noted that this cluster consists of only three countries. In terms of the number of observations, the countries in the third cluster represent only 6% of the total sample (3,344 observations).

On the other hand, the second cluster, which serves as the reference group, includes 331 firms and accounts for approximately 80% of the total sample. The slope coefficients of the independent variables in the first cluster do not significantly differ from those of the reference group, indicating that the firms in this group are affected by the independent variables in a similar manner to those in the reference cluster.

Following the presentation of the empirical findings, this section marks the transition to the concluding part of the thesis, where the key results are interpreted in the context of the existing literature. It outlines the main conclusions drawn from the analysis and provides practical and theoretical recommendations based on the observed patterns. The section begins by summarizing the primary insights regarding the determinants of systematic risk, followed by a discussion of their implications for investors, policymakers, and researchers.

CHAPTER V

FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

The findings of this thesis present an important step forward in understanding the determinants of systematic risk in developed markets. By employing the fundamental beta Capital Asset Pricing Model (CAPM) approach, this research sheds light on the relationship between firm-specific variables and market risk, thus contributing to the broader literature on financial decision-making and risk management.

In this section, the results of the research will be explained and recommendations will be given.

Key Findings According to Fixed Effect Model

All findings are gathered from fixed effect model used in this study. The results underscore that firm-specific variables significantly influence systematic risk, as represented by the beta coefficient. Among these variables, several critical insights were observed:

A negative and significant relationship between asset turnover (at) and beta suggests that firms with higher asset efficiency face lower exposure to systematic risk. This is consistent with the logic that efficient asset utilization reflects stable operations and robust management practices, which can insulate firms against market fluctuations. The asset turnover ratio, which captures how effectively a firm uses its total assets to generate revenue, serves as a key indicator of operational performance. A higher ratio suggests that a company is utilizing its assets efficiently to drive sales, which can contribute to financial stability and reduce vulnerability to external market fluctuations. This negative relationship between asset turnover and systematic risk aligns with the argument that firms managing their resources more effectively tend to exhibit lower volatility in earnings and are perceived as less risky by investors. It is argued that firms with strong asset management practices are generally subject to lower levels of systematic risk, as they are better equipped to weather market uncertainties and generate consistent returns. Moreover, firms with high asset turnover can often recover more quickly from past losses and may require less reliance on external financing, both of which further decrease their exposure to systematic market movements. This interpretation is reinforced in literature as well, and noted that although aggressive growth strategies can sometimes inflate profitability, efficiency-oriented strategies tend to promote more sustainable and less volatile performance, ultimately reducing systematic risk. The observed statistically significant and negative coefficient of At in the current study suggests that improving operational efficiency through better asset utilization not only enhances profitability but also contributes to a firm's risk mitigation. High turnover implies that each unit of asset is generating substantial revenue, which stabilizes earnings and reduces the firm's beta. In conclusion, this result emphasizes the role of asset turnover as more than just a performance metric; it also serves as a predictor of how resilient a company may be in the face of broader market risks. Efficient asset use helps to shield firms from adverse market conditions, making them more attractive to risk-averse investors and contributing to a lower level of systematic risk.

The negative relationship between dividend per share (logdps) and systematic risk highlights the signaling effect of stable dividend distributions. Companies with consistent and predictable dividend policies are perceived as less risky by investors, reinforcing their ability to weather adverse market conditions. This aligns with existing literature, emphasizing dividends as a signal of stability and financial health. This finding supports the view that higher dividend payouts are associated with lower levels of systematic risk. Since beta reflects a firm's sensitivity to market fluctuations, the observed negative relationship suggests that firms distributing higher dividends per share are generally perceived as less risky by investors. One reason for this may be the signaling effect of dividend policies. When a company pays consistent and higher dividends, it often conveys financial stability and confidence in future earnings, which helps reduce uncertainty and stock price volatility. Additionally, dividend income is considered more predictable than capital gains, further reinforcing investor confidence. Dividend policy can also serve as an indicator of a firm's overall risk profile. Firms with regular dividend distributions are often viewed as operating in stable environments or maintaining strong governance practices, both of which contribute to a lower beta. In contrast, firms with irregular or minimal dividends may be seen as riskier due to financial instability or uncertain strategic directions. This relationship may also vary depending on sectoral dynamics and a firm's capital structure. In some cases, particularly for highly leveraged firms, dividend increases can signal confidence in debt management, which may reduce systematic risk. Conversely, in more volatile industries, low or absent dividend payments may be linked to higher beta values due to growth-oriented but uncertain investment strategies. In sum, the analysis reinforces the idea that stable and strong dividend payouts not only reflect financial performance but also function as a mechanism for reducing a firm's exposure to systematic market risks.

The positive correlation between earnings before interest and taxes (logebit) and systematic risk highlights that profit-based business growth, as measured by earnings before interest and taxes (EBIT), may be associated with an increase in systematic risk. While growth generally indicates positive performance and expansion in scale, it can also bring operational complexity, increased financing needs, and heightened exposure to market volatility. Firms experiencing rapid profit growth often require significant resources to sustain that expansion, which may lead to greater reliance on debt and higher return volatility. As companies grow larger and more complex, they may also become more vulnerable to external shocks, competitive pressures, and macroeconomic fluctuations. These dynamics help explain the observed positive relationship between ebit growth and systematic risk in this research. Although some perspectives suggest that rising profits could be interpreted as a sign of effective management and reduced risk, the results here support the view that aggressive or large-scale profit growth may increase a firm’s sensitivity to market movements. Therefore, while growth is beneficial, it may also carry additional risk when not managed with adequate control mechanisms. In summary, the positive and significant coefficient for logebit indicates that rapid or extensive profit growth can contribute to a higher level of systematic risk, especially when accompanied by financial and operational complexity.

Larger firms, as indicated by total assets (logta), demonstrated greater exposure to systematic risk. This finding reflects the increased complexity and market dependencies of large firms, which make them more susceptible to global and macroeconomic factors. This finding adds to the ongoing discussion about the relationship between firm size and systematic risk. While it is commonly believed that larger firms benefit from economies of scale, diversified operations, and a greater ability to withstand external shocks—thus reducing their sensitivity to market movements—the current result suggests a different pattern. The positive and significant relationship observed between total assets and systematic risk indicates that larger firms may, in fact, be more exposed to market volatility. This may be due to the increased complexity of operations, higher fixed costs, or greater visibility in financial markets that come with firm expansion. In such cases, growing size can amplify financial vulnerability rather than mitigate it. Over time, structural changes in how firms operate and finance their activities may have altered traditional risk dynamics. Larger companies may now rely more heavily on debt or make sizable investments that increase their sensitivity to market conditions. Although some views suggest that size alone may not directly influence systematic risk, the current analysis highlights that firm size—especially when accompanied by operational and financial complexity—can be positively associated with beta. In conclusion, while the relationship between size and risk is nuanced, the findings support the idea that increases in firm scale do not always translate to reduced market risk, and may, under certain conditions, contribute to higher systematic risk levels.

The relationship between leverage (liabilities to assets ratio - lta) and beta was positive and statistically significant. This indicates that while financial leverage theoretically increases systematic risk, its actual impact may vary depending on firm-specific contexts, industry dynamics, and economic conditions. The liabilities-to-assets ratio, as an indicator of how much debt a firm uses to finance its operations, reflects the firm's exposure to financial obligations. An increase in this ratio typically signals higher financial risk, particularly under volatile market conditions where debt repayments may become more burdensome. Although theoretical models argue that capital structure might not influence risk in ideal market settings, real-world conditions—such as taxes, bankruptcy costs, and imperfect information—make leverage a critical factor in determining a firm's risk profile. The positive and statistically significant coefficient for leverage in this study indicates that firms with higher debt relative to assets tend to be more sensitive to market fluctuations. This relationship can be explained by the amplifying effect of fixed debt payments on earnings volatility. Higher leverage can magnify both returns and losses, making firms more vulnerable to external shocks. Additionally, firms with high leverage may intentionally take on more risk in pursuit of higher returns, further reinforcing their exposure to systematic risk. Overall, the findings emphasize that leverage is not only a financial decision but also a strategic factor influencing a firm's market risk. For both investors and managers, understanding the implications of leverage is essential for evaluating and managing exposure to systematic fluctuations.

Return on assets (roa) displayed a negative and significant relationship with systematic risk. This reinforces the notion that profitability acts as a buffer against market turbulence, as higher returns provide financial flexibility and stability. This finding supports the view that higher profitability is associated with lower levels of systematic risk. Profitability ratios such as Return on Assets (ROA) reflect a firm's efficiency in generating earnings from its assets, which in turn signals operational strength and financial resilience. A higher ROA suggests that the firm is better positioned to withstand external shocks and maintain stable performance. The observed negative and significant relationship between ROA and systematic risk reinforces the idea that profitability acts as a stabilizing factor. Firms that consistently generate income are less vulnerable to market volatility and tend to be perceived as more reliable and less risky by investors. As a result, these firms typically exhibit lower beta values, indicating reduced sensitivity to market-wide movements. Overall, this result highlights that profitability is not only a performance indicator but also a key determinant of a firm's perceived risk in financial markets. Strong and stable returns contribute to investor confidence and help mitigate exposure to systematic risk.

The results of the cluster analysis indicate that the influence of independent variables on systematic risk (beta) varies significantly across different subgroups within the sample. While the overall sample reveals a negative and statistically significant relationship between dividend payouts and systematic risk, this relationship reverses in the third cluster. In this specific group, dividend payouts are positively associated with systematic risk, suggesting that under certain firm profiles or contextual conditions, higher dividends may reflect increased market sensitivity rather than stability.

A similar divergence is observed in the relationship between profitability and systematic risk. Although the full sample analysis suggests a negative association—implying that more profitable firms tend to exhibit lower systematic risk—this effect intensifies in the third cluster. The stronger negative relationship suggests that, for these firms, profitability plays an even more critical role in mitigating exposure to market fluctuations.

Firm size, proxied by total assets, also demonstrates a shift in influence across clusters. In the main sample, a positive relationship is found between firm size and systematic risk, indicating that larger firms may be more exposed to market volatility. However, in the third cluster, this relationship turns negative, highlighting that for certain firms, increased size may contribute to greater resilience rather than added risk.

The leverage ratio, represented by the liabilities-to-assets measure, maintains a positive relationship with systematic risk across the sample. Yet, this relationship becomes substantially stronger in the third cluster. This suggests that financial leverage contributes more significantly to market risk within this subgroup, potentially due to heightened sensitivity to debt servicing or external financing constraints.

These findings demonstrate that the effects of key financial variables on systematic risk are not homogeneous across firms. The direction and strength of relationships vary by cluster, highlighting the value of disaggregated analysis. Segmenting the sample through hierarchical clustering uncovers important nuances, emphasizing that firm-specific or contextual characteristics play a critical role in shaping risk dynamics.

The distinctive patterns observed in the third cluster suggest that the firms within this group possess structural and financial characteristics that set them apart from the broader sample. Unlike firms in the other clusters, these entities appear to operate under conditions that invert or intensify typical financial relationships with systematic risk. The reversal of the dividend payout effect may indicate that, for these firms, higher dividends are not necessarily perceived as signals of stability but perhaps as reflections of limited reinvestment capacity or elevated exposure to external expectations. The intensified negative relationship between profitability and risk suggests that maintaining profitability is especially critical for these firms, possibly due to tighter margins or greater vulnerability to shocks. The shift in the firm size coefficient from positive to negative implies that, contrary to the general assumption, increased scale in these firms may contribute to operational flexibility and risk absorption rather than higher exposure. At the same time, the stronger positive impact of leverage indicates a heightened sensitivity to financial structure, suggesting that these firms may rely more heavily on debt financing or operate under more volatile credit conditions. Collectively, these characteristics portray a cluster of firms for which financial decisions—particularly around profitability, leverage, and payout policy—have more pronounced and sometimes counterintuitive implications for market risk.

Key Findings According to Cluster Analysis

Countries in Cluster 1 are characterized by more developed and stable economies, defined by high levels of dividend per share (logdps) and return on assets (roa). These countries are strong in dividend payments and adopt a cautious approach to financial stability. This cluster aligns with the high levels of logta and roa observed in Cluster 1.

Notably, countries like Australia, Germany, and Japan are prominently represented in this cluster, with Japan standing out as the most represented country with 50 observations. Additionally, the United Kingdom (7 observations) and the United States

(6 observations) are significant representatives in Cluster 1, further emphasizing the importance of this group.

Countries in Cluster 2 are characterized by larger, industrialized infrastructures with high logebit and logta values, but they tend to rely more heavily on debt. This cluster represents growth-oriented nations that prioritize expansion through leveraging debt. Cluster 2 is predominantly represented by major developed economies such as Japan (86 observations), the United States (99 observations), and the United Kingdom (25 observations). These countries exemplify the traits of large, industrialized, and diversified economies within this group.

Additionally, countries like Switzerland (18 observations), Germany (24 observations), and Australia (25 observations) also have a significant presence in Cluster 2, further highlighting its industrial and financial diversity.

Countries in Cluster 3 are cautious, prioritizing liquidity and aiming for growth with minimal debt. This cluster is associated with high qr and lta values, reflecting a focus on achieving greater financial stability. However, Cluster 3 has very limited representation, with only Japan (1 observation) and Canada (2 observations) being notable members.

The distinctive economic structures of the countries in Cluster 3 may explain its low representation, suggesting that this cluster captures nations with unique financial and economic characteristics, differing significantly from the other clusters.

This thesis contributes to a deeper understanding of systematic risk in developed markets by highlighting the role of firm-specific variables. It challenges traditional risk models by demonstrating that factors such as asset turnover, profitability, and dividend policies play a critical role in shaping risk profiles. This study examines the impact of firm-specific factors on systematic risk within the industrial sector of developed countries. The findings contribute to the understanding of how internal firm characteristics influence risk exposure in this sector.

Future research could expand upon this study by incorporating accounting beta, as introduced in the seminal work of Beaver, Kettler, and Scholes (1970), to provide a more comprehensive assessment of systematic risk determinants.

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APPENDICES

Model Summary

Algorithm	TwoStep
Inputs	7
Clusters	3

Cluster Quality

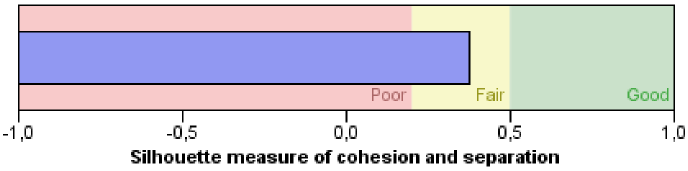


Figure 5. Cluster Analysis Model Summary

Table 20.

Cluster Groups

Number of Cases in each Cluster		
Cluster	1	84,000
	2	331,000
	3	3,000
Valid		418,000
Missing		,000

Table 21.

Agglomeration Schedule

Agglomeration Schedule						
	Cluster Combined			Stage Cluster First Appears		
Stage	Cluster 1	Cluster 2	Coefficients	Cluster 1	Cluster 2	Next Stage
1	44	302	,000	0	0	296
2	68	320	,003	0	0	168
3	9	12	,009	0	0	233
4	7	65	,018	0	0	43
5	214	343	,028	0	0	131
6	161	418	,039	0	0	121
7	266	400	,052	0	0	158
8	52	145	,066	0	0	150
9	372	393	,081	0	0	37
10	100	195	,096	0	0	162
11	277	392	,111	0	0	42
12	167	370	,126	0	0	56
13	157	178	,143	0	0	48
14	303	305	,161	0	0	192
15	2	321	,178	0	0	96
16	96	107	,196	0	0	134
17	247	348	,213	0	0	152
18	363	384	,232	0	0	231
19	82	387	,251	0	0	230
20	132	152	,270	0	0	59
21	139	162	,291	0	0	120
22	268	330	,312	0	0	118
23	38	142	,334	0	0	64
24	141	273	,357	0	0	215
25	148	183	,382	0	0	111
26	149	295	,407	0	0	72

27	275	375	,432	0	0	151
28	57	358	,458	0	0	117
29	129	364	,486	0	0	243
30	165	338	,513	0	0	190
31	102	108	,542	0	0	106
32	123	136	,572	0	0	123
33	380	412	,602	0	0	173
34	41	43	,632	0	0	274
35	106	153	,664	0	0	144
36	10	308	,695	0	0	131
37	354	372	,728	0	9	97
38	249	324	,762	0	0	153
39	190	192	,796	0	0	187
40	232	353	,830	0	0	89
41	347	368	,865	0	0	75
42	277	319	,899	11	0	118
43	7	287	,934	4	0	227
44	155	280	,970	0	0	145
45	344	403	1,006	0	0	90
46	121	408	1,042	0	0	154
47	31	365	1,079	0	0	91
48	157	359	1,116	13	0	61
49	77	362	1,155	0	0	81
50	87	294	1,193	0	0	174
51	70	99	1,232	0	0	211
52	208	209	1,272	0	0	94
53	176	224	1,312	0	0	310
54	259	394	1,353	0	0	78
55	267	378	1,394	0	0	147
56	167	278	1,435	12	0	149
57	135	164	1,476	0	0	87
58	252	262	1,517	0	0	199

59	132	151	1,560	20	0	218
60	396	415	1,603	0	0	117
61	157	281	1,647	48	0	160
62	346	356	1,690	0	0	169
63	97	137	1,734	0	0	99
64	38	42	1,778	23	0	225
65	174	334	1,824	0	0	122
66	25	163	1,869	0	0	225
67	127	180	1,915	0	0	151
68	105	215	1,961	0	0	319
69	78	317	2,007	0	0	156
70	198	241	2,053	0	0	213
71	217	257	2,100	0	0	167
72	149	200	2,148	26	0	277
73	126	131	2,197	0	0	288
74	4	13	2,246	0	0	290
75	347	381	2,297	41	0	216
76	14	234	2,348	0	0	236
77	197	383	2,401	0	0	245
78	83	259	2,454	0	54	273
79	29	255	2,508	0	0	199
80	130	150	2,562	0	0	100
81	55	77	2,616	0	49	218
82	117	182	2,671	0	0	129
83	140	191	2,726	0	0	148
84	314	399	2,782	0	0	307
85	134	289	2,838	0	0	189
86	73	171	2,895	0	0	197
87	135	397	2,952	57	0	240
88	23	311	3,009	0	0	167
89	231	232	3,068	0	40	109
90	225	344	3,128	0	45	203

91	31	293	3,189	47	0	292
92	256	292	3,249	0	0	143
93	120	124	3,310	0	0	177
94	186	208	3,371	0	52	242
95	101	116	3,433	0	0	294
96	2	385	3,495	15	0	257
97	354	373	3,558	37	0	166
98	146	173	3,622	0	0	144
99	97	128	3,687	63	0	162
100	130	147	3,751	80	0	287
101	179	187	3,817	0	0	263
102	177	296	3,883	0	0	237
103	71	250	3,952	0	0	272
104	254	304	4,021	0	0	145
105	248	274	4,090	0	0	156
106	102	181	4,162	31	0	228
107	122	228	4,234	0	0	229
108	50	66	4,307	0	0	182
109	231	361	4,379	89	0	169
110	322	389	4,453	0	0	336
111	148	160	4,527	25	0	293
112	340	341	4,602	0	0	138
113	53	360	4,677	0	0	270
114	284	327	4,752	0	0	168
115	67	111	4,828	0	0	222
116	196	261	4,904	0	0	309
117	57	396	4,981	28	60	200
118	268	277	5,059	22	42	227
119	86	115	5,137	0	0	177
120	138	139	5,217	0	21	264
121	161	207	5,299	6	0	250
122	158	174	5,381	0	65	253

123	123	125	5,463	32	0	192
124	5	32	5,545	0	0	340
125	40	219	5,627	0	0	254
126	168	172	5,711	0	0	249
127	328	382	5,794	0	0	280
128	15	233	5,878	0	0	238
129	117	144	5,964	82	0	228
130	154	203	6,050	0	0	155
131	10	214	6,137	36	5	164
132	235	288	6,225	0	0	333
133	351	374	6,313	0	0	231
134	96	220	6,401	16	0	163
135	309	345	6,490	0	0	275
136	349	371	6,580	0	0	268
137	377	410	6,670	0	0	270
138	1	340	6,760	0	112	172
139	98	113	6,851	0	0	226
140	316	414	6,942	0	0	214
141	64	299	7,035	0	0	267
142	24	318	7,128	0	0	258
143	256	258	7,223	92	0	215
144	106	146	7,319	35	98	190
145	155	254	7,415	44	104	275
146	8	279	7,511	0	0	236
147	267	290	7,607	55	0	185
148	140	216	7,704	83	0	282
149	167	276	7,802	56	0	226
150	52	202	7,899	8	0	251
151	127	275	7,998	67	27	208
152	61	247	8,097	0	17	204
153	75	249	8,197	0	38	314
154	121	306	8,300	46	0	211

155	51	154	8,404	0	130	252
156	78	248	8,508	69	105	165
157	28	210	8,612	0	0	221
158	266	310	8,719	7	0	180
159	114	175	8,825	0	0	262
160	157	357	8,934	61	0	242
161	104	110	9,042	0	0	263
162	97	100	9,152	99	10	330
163	96	211	9,263	134	0	264
164	10	48	9,375	131	0	351
165	78	369	9,487	156	0	272
166	189	354	9,599	0	97	230
167	23	217	9,713	88	71	291
168	68	284	9,829	2	114	258
169	231	346	9,945	109	62	316
170	265	301	10,063	0	0	213
171	388	398	10,182	0	0	240
172	1	417	10,301	138	0	297
173	332	380	10,420	0	33	268
174	87	264	10,543	50	0	261
175	21	84	10,666	0	0	259
176	62	406	10,792	0	0	237
177	86	120	10,920	119	93	191
178	59	222	11,048	0	0	269
179	238	315	11,177	0	0	244
180	266	405	11,305	158	0	250
181	76	242	11,435	0	0	346
182	50	411	11,565	108	0	266
183	156	260	11,695	0	0	301
184	18	205	11,826	0	0	357
185	239	267	11,957	0	147	283
186	60	218	12,089	0	0	244

187	58	190	12,222	0	39	253
188	193	194	12,356	0	0	276
189	134	166	12,491	85	0	210
190	106	165	12,628	144	30	243
191	86	119	12,765	177	0	282
192	123	303	12,903	123	14	285
193	367	413	13,042	0	0	315
194	325	395	13,182	0	0	365
195	22	333	13,322	0	0	234
196	229	337	13,465	0	0	283
197	73	92	13,609	86	0	319
198	27	286	13,753	0	0	303
199	29	252	13,898	79	58	332
200	57	391	14,045	117	0	257
201	323	342	14,195	0	0	295
202	30	226	14,347	0	0	329
203	225	339	14,498	90	0	278
204	61	240	14,651	152	0	280
205	335	386	14,803	0	0	360
206	350	390	14,956	0	0	370
207	285	352	15,109	0	0	300
208	74	127	15,267	0	151	262
209	212	221	15,426	0	0	350
210	134	251	15,585	189	0	232
211	70	121	15,744	51	154	260
212	37	312	15,906	0	0	286
213	198	265	16,069	70	170	320
214	3	316	16,232	0	140	290
215	141	256	16,396	24	143	291
216	347	409	16,563	75	0	266
217	89	336	16,735	0	0	269
218	55	132	16,908	81	59	287

219	244	245	17,083	0	0	271
220	72	253	17,259	0	0	252
221	28	88	17,435	157	0	284
222	67	93	17,612	115	0	279
223	26	49	17,790	0	0	274
224	56	69	17,968	0	0	289
225	25	38	18,150	66	64	285
226	98	167	18,335	139	149	331
227	7	268	18,520	43	118	299
228	102	117	18,705	106	129	354
229	85	122	18,894	0	107	292
230	82	189	19,085	19	166	251
231	351	363	19,283	133	18	334
232	134	201	19,481	210	0	338
233	9	404	19,681	3	0	316
234	22	298	19,885	195	0	246
235	47	184	20,098	0	0	333
236	8	14	20,315	146	76	323
237	62	177	20,533	176	102	309
238	15	34	20,753	128	0	308
239	109	185	20,975	0	0	356
240	135	388	21,200	87	171	299
241	20	170	21,424	0	0	326
242	157	186	21,649	160	94	325
243	106	129	21,875	190	29	324
244	60	238	22,105	186	179	335
245	197	271	22,336	77	0	315
246	22	283	22,569	234	0	329
247	402	407	22,805	0	0	314
248	366	416	23,045	0	0	313
249	168	307	23,288	126	0	317
250	161	266	23,532	121	180	300

251	52	82	23,777	150	230	307
252	51	72	24,029	155	220	277
253	58	158	24,282	187	122	342
254	40	263	24,535	125	0	323
255	33	355	24,790	0	0	327
256	46	90	25,045	0	0	318
257	2	57	25,304	96	200	295
258	24	68	25,564	142	168	273
259	21	230	25,826	175	0	325
260	19	70	26,090	0	211	355
261	87	379	26,358	174	0	349
262	74	114	26,629	208	159	288
263	104	179	26,912	161	101	286
264	96	138	27,199	163	120	324
265	35	326	27,487	0	0	337
266	50	347	27,778	182	216	296
267	63	64	28,072	0	141	321
268	332	349	28,368	173	136	297
269	59	89	28,668	178	217	294
270	53	377	28,971	113	137	335
271	244	269	29,276	219	0	302
272	71	78	29,586	103	165	362
273	24	83	29,899	258	78	380
274	26	41	30,213	223	34	358
275	155	309	30,540	145	135	330
276	193	291	30,868	188	0	303
277	51	149	31,204	252	72	306
278	225	401	31,541	203	0	341
279	67	236	31,886	222	0	372
280	61	328	32,234	204	127	351
281	237	297	32,583	0	0	366
282	86	140	32,941	191	148	320

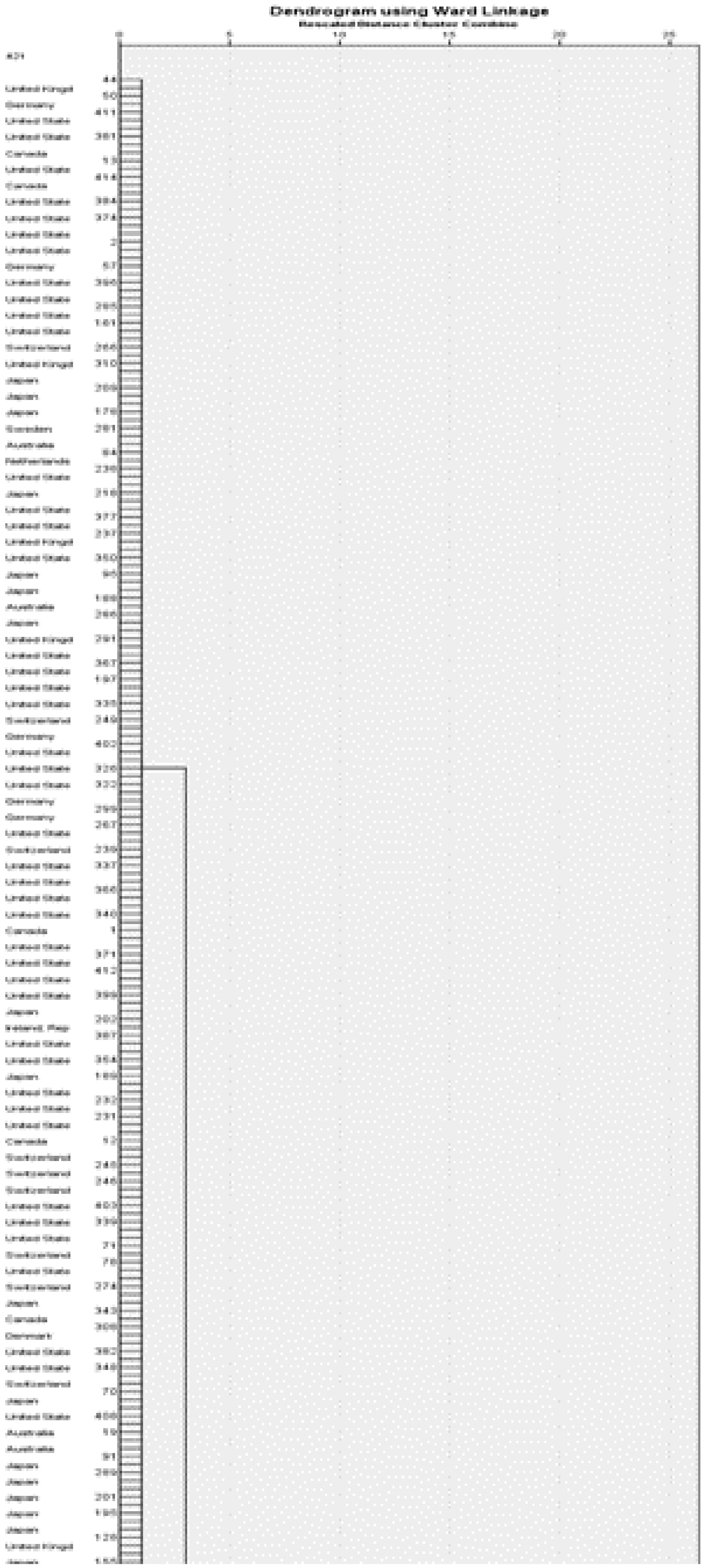
283	229	239	33,304	196	185	321
284	16	28	33,670	0	221	301
285	25	123	34,040	225	192	331
286	37	104	34,415	212	263	344
287	55	130	34,790	218	100	293
288	74	126	35,168	262	73	342
289	56	81	35,550	224	0	328
290	3	4	35,931	214	74	373
291	23	141	36,322	167	215	347
292	31	85	36,718	91	229	348
293	55	148	37,118	287	111	347
294	59	101	37,525	269	95	322
295	2	323	37,935	257	201	334
296	44	50	38,346	1	266	377
297	1	332	38,763	172	268	363
298	95	169	39,195	0	0	353
299	7	135	39,632	227	240	371
300	161	285	40,086	250	207	361
301	16	156	40,546	284	183	332
302	244	246	41,007	271	0	359
303	27	193	41,479	198	276	386
304	118	223	41,953	0	0	390
305	300	313	42,429	0	0	357
306	39	51	42,906	0	277	345
307	52	314	43,386	251	84	352
308	15	103	43,880	238	0	345
309	62	196	44,381	237	116	349
310	45	176	44,887	0	53	344
311	17	227	45,395	0	0	358
312	94	206	45,905	0	0	356
313	272	366	46,416	0	248	365
314	75	402	46,941	153	247	360

315	197	367	47,473	245	193	327
316	9	231	48,006	233	169	352
317	36	168	48,540	0	249	369
318	46	213	49,081	256	0	350
319	73	105	49,630	197	68	354
320	86	198	50,181	282	213	376
321	63	229	50,747	267	283	336
322	54	59	51,314	0	294	374
323	8	40	51,888	236	254	348
324	96	106	52,471	264	243	339
325	21	157	53,060	259	242	361
326	20	199	53,659	241	0	364
327	33	197	54,286	255	315	379
328	56	331	54,933	289	0	391
329	22	30	55,591	246	202	394
330	97	155	56,270	162	275	338
331	25	98	56,961	285	226	371
332	16	29	57,660	301	199	376
333	47	235	58,381	235	132	367
334	2	351	59,126	295	231	373
335	53	60	59,885	270	244	384
336	63	322	60,692	321	110	381
337	35	329	61,509	265	0	395
338	97	134	62,327	330	232	383
339	96	243	63,161	324	0	368
340	5	91	64,003	124	0	355
341	225	376	64,864	278	0	375
342	58	74	65,733	253	288	382
343	133	188	66,609	0	0	353
344	37	45	67,508	286	310	369
345	15	39	68,421	308	306	372
346	76	80	69,349	181	0	391

347	23	55	70,366	291	293	382
348	8	31	71,392	323	292	383
349	62	87	72,424	309	261	390
350	46	212	73,458	318	209	374
351	10	61	74,537	164	280	362
352	9	52	75,641	316	307	363
353	95	133	76,759	298	343	370
354	73	102	77,905	319	228	368
355	5	19	79,078	340	260	385
356	94	109	80,290	312	239	389
357	18	300	81,517	184	305	378
358	17	26	82,856	311	274	367
359	244	270	84,261	302	0	387
360	75	335	85,745	314	205	379
361	21	161	87,252	325	300	393
362	10	71	88,773	351	272	375
363	1	9	90,369	297	352	403
364	20	79	91,985	326	0	388
365	272	325	93,634	313	194	381
366	237	282	95,340	281	0	384
367	17	47	97,086	358	333	394
368	73	96	98,843	354	339	400
369	36	37	100,611	317	344	378
370	95	350	102,391	353	206	407
371	7	25	104,187	299	331	380
372	15	67	106,089	345	279	388
373	2	3	108,197	334	290	377
374	46	54	110,352	350	322	398
375	10	225	112,578	362	341	387
376	16	86	114,864	332	320	392
377	2	44	117,226	373	296	397
378	18	36	119,758	357	369	398

379	33	75	122,340	327	360	386
380	7	24	124,947	371	273	399
381	63	272	127,689	336	365	395
382	23	58	130,442	347	342	392
383	8	97	133,331	348	338	385
384	53	237	136,391	335	366	393
385	5	8	139,560	355	383	404
386	27	33	142,750	303	379	407
387	10	244	146,220	375	359	403
388	15	20	149,697	372	364	401
389	94	204	153,275	356	0	396
390	62	118	156,910	349	304	399
391	56	76	160,866	328	346	400
392	16	23	164,830	376	382	401
393	21	53	168,883	361	384	397
394	17	22	173,618	367	329	406
395	35	63	179,139	337	381	411
396	94	112	185,156	389	0	408
397	2	21	191,695	377	393	413
398	18	46	198,817	378	374	405
399	7	62	206,051	380	390	404
400	56	73	213,592	391	368	405
401	15	16	223,568	388	392	406
402	6	11	233,569	0	0	410
403	1	10	244,815	363	387	409
404	5	7	256,784	385	399	409
405	18	56	270,142	398	400	412
406	15	17	283,905	401	394	412
407	27	95	299,808	386	370	413
408	94	159	318,821	396	0	415
409	1	5	342,790	403	404	411
410	6	143	370,927	402	0	417

411	1	35	417,708	409	395	414
412	15	18	466,758	406	405	415
413	2	27	521,467	397	407	414
414	1	2	591,876	411	413	416
415	15	94	699,228	412	408	416
416	1	15	929,805	414	415	417
417	1	6	2936,571	416	410	0


Dendrogram using Ward Linkage
Rescaled Distance Cluster Combine
0
5
10
15
20
25

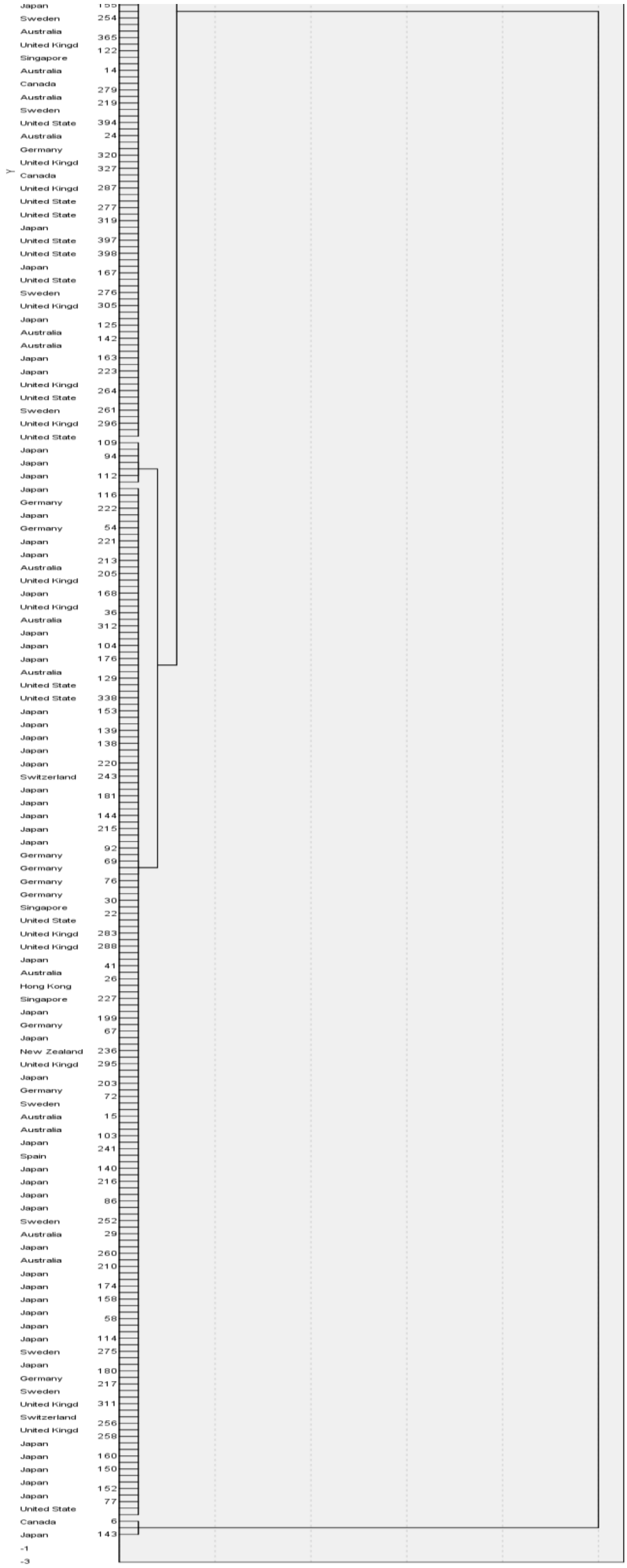


Figure 6. Dendogram Graph