Assessing the Impact of Board Structure on S&P 500 Companies' Performance

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4th Year Project Report
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2024

Abstract

Scholars and industry experts have created various frameworks in the interests of measuring the quality of corporate governance. Research indicates that the connection between corporate governance quality and performance can be positive, non-existent, and in some cases, negative and that despite the methodological limitations of current governance metrics, they remain widely used today. Therefore, in seeking to explore this complex relationship, this research creates a data pipeline to perform an innovative methodology, through the construction of an alternative corporate governance index using Multi-Criteria Decision Analysis. Furthermore, to examine the evolution of the quality-performance correlation, Cluster and Factor Analyses were implemented as part of the data pipeline.

This paper presents the results of three research objectives. Firstly, the creation of a robust data pipeline for future board structure research, with data collected from WRDS, processed using Python scripts and automated using Apache Airflow. The second objective proves that MCDA can be a useful tool for future corporate governance research, displaying a weak, yet positive correlation with Tobin's Q and showing robustness through sensitivity testing. The results of the third objective focus on the underlying factors significantly contributing to firm performance and provide useful insights into the complex relationship between board structure and firm performance.

Research Ethics Approval

This project was planned in accordance with the Informatics Research Ethics policy. It did not involve any aspects that required approval from the Informatics Research Ethics committee.

Declaration

I declare that this thesis was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

(*Toby Whittome*)

Acknowledgements

I would like to extend my gratitude to my project supervisor, Felipe Costa Sperb for all the guidance along the way.

I would also like to thank Yong Chen for allowing the use of his a Airflow pipeline to automate functions in this project.

Finally, thank you to my friends and family for all the support.

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Chapter 1

Introduction

1.1 Motivation

Environmental, social and corporate governance (ESG) factors are becoming increasingly popular within investing and academic research within this field can yield great potential business advantage. ESG factors include environmental considerations, social factors, and governance factors (Conca et al., 2021).

Sustainable investment strategy has gained attention as the challenges of environmental degradation, resource depletion and climate change become increasingly relevant in the public eye (Pástor et al., 2021). In 2021, ESG-focused portfolios managed almost $40 trillion USD and are expected to reach $53 trillion USD by 2025, representing a third of the total assets under management globally (Cruz and Matos, 2023). Therefore, incorporating ESG strategy allows for long-term sustainability and ethical considerations to be quantified for future investment decisions (Busch et al., 2016).

The G of ESG stands for *corporate governance*, which encompasses the control mechanisms designed to protect the interests of investors and shareholders by addressing the potential conflicts that arise when managers' goals diverge from those of the shareholders. Studies in this field are dedicated to identifying effective governance strategies to ensure alignment between the objectives of decision-makers and the interests of shareholders. Such mechanisms are important in enhancing transparency, corporate performance and boosting shareholder value (Gul et al., 2003). Consequently, a significant portion of research into corporate governance focuses on measuring how these mechanisms affect firm performance.

Traditionally, corporate governance analysis has been one dimensional, analysing singular variables on firm performance using simple linear regressions. However, current work has shifted to using "composite measures" of governance to reflect the possibility of interplay among the characteristics. Labelle was one of the pioneering writers to explore the link between corporate governance and performance through a multidimensional variable (2002). This led to a proliferation of attempts to synthesise individual variable research into governance scores, meant to reflect the governance quality more holistically. Firstly the G-index, which quantifies the level of shareholder rights and corporate governance within firms, encapsulates the notion that ”stronger shareholder rights lead to higher firm valuation” (Gompers et al., 2003). A notable limitation of the G-index is its broad scope, which, while comprehensive, may overlook the impact of specific governance practices. Similarly, the E-index, a refinement of the G-index (Bebchuk et al., 2009), further explains the corporate governance mechanisms that are most significant in affecting firm value, thus emphasising the critical role governance plays in corporate performance.

A number of corporate governance scores have also been created by various well-known data providers, including Bloomberg, Thomson Reuters, Standard and Poor, the Globe and Mail Report and the Institutional Shareholder Governance Index, as well as investments banks such as Morgan Stanley Capital International. However, these indices showcase significant differences in opinions (Chatterji et al., 2016; Berg et al., 2022) and considerable ”confusion” among academics regarding their methods transparency (Amel-Zadeh and Serafeim, 2018). The complexity of governance data and the lack of standardisation makes it difficult to compare companies on these metrics. They are often proprietary, as they are scored on the risks of their particular model. Therefore, this project aims to address these issues associated with governance metric creation transparency, providing detailed insight into the formation of a corporate governance index. Globally, regulators are working to improve the transparency of governance information by mandating that companies disclose them alongside their financials, but this is still materialising (Securities and Commission, 2022).

Using MCDA, this dissertation aims to implement a novel approach that bridges the observed gaps in prior research. Drawing inspiration from the G-index, the metric will integrate a wide array of board structure variables most closely tied to performance outcomes, thus mitigating the issue of potentially overlooking impactful board practices and ensuring relevance in analysis.

1.2 Research Objectives

This exploratory research assesses the impact of board structure on performance for S&P500 companies and has three main research objectives outlined below:

- **Objective 1: Develop a data pipeline to collect, preprocess and analyse corporate governance data.**

  Using the WRDS API, the latest data will be automatically collected and processed, providing a central table and analysis methods as tools for future research. An Airflow pipeline will allow the automation of the python scripts for future research.

- **Objective 2: Evaluate the effectiveness of Multi-Criteria Decision Analysis in developing a governance score that can indicate performance.**

  Multi-Criteria-Decision Analysis (MCDA) will be used to create a score for the companies based off the board structure criteria. This will provide academics with valuable insights and facilitate the decision-making processes of investors.

As a novel approach in this context, evaluating its effectiveness is important to help guide future work in the field of corporate governance.

- **Objective 3: Identify the underlying factors that significantly contribute to company performance, and analyse how companies can be classified based on their board structure traits.**

  Factor Analysis will be used to both reduce the high dimensionality of the dataset and discover latent variables to explain the correlation with performance. Cluster Analysis will facilitate discussion of how specific characteristics impact performance for different groups of companies, deepening the understanding of how governance structures influence corporate performance.

1.3 Structure Overview

This dissertation begins by introducing the corporate governance landscape in Chapter 1, outlining the motivation behind this work as well as the research objectives it aims to achieve. Chapter 2 provides a comprehensive review of the literature surrounding each of the variables chosen to be in the MCDA. It also includes the reasoning behind adopting Tobin's Q as the performance metric. Following this, Chapter 3 is structured as follows: it begins with the first methodology, immediately followed by its results, before transitioning to the second methodology and its results, and so on, using this structure for each analysis (MCDA, Cluster and Factor). This methodical arrangement should provide more clarity than a traditional one, which clumps the methodologies and results together.

Chapter 4 synthesises the research chapter's findings to address the results in terms of the three objectives defined in the introduction. This is followed by a holistic overview of the study's achievements with regards to the current literature. Finally, a critical evaluation is included, addressing the project's limitations and challenges. The paper finishes with Chapter 5, which contains a summary of the findings and discussions, coupled with propositions for future research.

Chapter 2

Background

2.1 Literature review

This paper studies nine variables which are central to board structure and corporate governance governance to examine their individual significance against a backdrop of prior research, as outlined below. This process informs the weights assigned to each variable in the Multi-Criteria Decision Analysis.

2.1.1 Board size

Board size is a critical characteristic influencing a company's governance dynamics, affecting decision-making processes, power distribution, and overall board effectiveness. Previous research and theories have provided various results. Firstly, Lipton, Lorsch and Jensen find that that smaller boards do better due to the productivity loss associated with large groups (1992; 1993). By contrast, others present how companies with larger boards perform better (Hillman and Dalziel, 2003; Dalton et al., 1999; Beiner et al., 2006). This aligns with Resource Dependence Theory, a theory that views the board as a resource provider where additional directors bring more human and social capital (Pfeffer, 1972). Although Holthausen and Larker fail to find evidence of size on performance (1993), the literature generally agrees that various characteristics of board composition affect firm's financial performance (Bhagat and Black, 1999; Duru et al., 2016).

It is important to consider that the number of directors on a board might arise endogenously as a function of other variables, such as company size, performance, or the CEO's preferences. For example, the managerial quality hypothesis of Byrd and Hickman argues that high-caliber CEOs may 'dress up their firms' boards with independent directors to give shareholders the appearance of active oversight (1992). One could also argue that effective CEOs prefer to have smaller boards around them, or the phenomenon where board sizes are reduced during periods of distress (Gilson, 1990).

2.1.2 Independent Non-Executive directors

While the empirical evidence on the impact of independent non-executive directors on firm performance is inconclusive, with some studies showing positive effects (Baysinger and Butler, 1985; Bruno and Claessens, 2010; Aggarwal et al., 2009; Pombo and Gutiérrez, 2011; Dahya et al., 2008; Jackling and Johl, 2009; Liu et al., 2015; Pearce and Zahra, 1992), others reporting non-significant relationships (Volonté, 2015; Hermalin and Weisbach, 1991; Villalonga and Amit, 2006), and some reporting a negative relationship (Bebchuk and Cohen, 2005; Muth and Donaldson, 1998; Klein et al., 2005; Shan and McIver, 2011). The theoretical underpinnings from Agency Theory suggest that independent directors are more likely to align with shareholder interests due to fewer conflicts of interest, thereby enhancing monitoring and strategic decision-making (Fama, 1980; García-Ramos and García-Olalla, 2011). Additionally, Resource Dependence Theory underscores the value of independent directors in providing external resources and insights crucial for strategic planning (Hillman and Dalziel, 2003; Daily and Dalton, 1994).

The importance of balancing board composition to include executive directors is recognised, as their intimate knowledge of company operations is essential for effective governance and information flow (Carpenter and Westphal, 2001; Donaldson and Davis, 2019). Complexity is also introduced as the level of independence differs. For example, some independent directors are purely independent while others have affiliations with the firm by virtue of their past employment relationships (Cavaco et al., 2017; Masulis et al., 2018). Despite these concerns, the consensus is that an increased proportion independent directors enhances board quality, positively impacting firm performance.

2.1.3 Board stock ownership

This research adopts the assumption that high board stock ownership positively impacts firm performance, as director shareholders have a vested interest in the firm's value to increase their own wealth. This aligning of director's interests with external shareholders improves firm oversight and performance (Shleifer and Vishny, 1989; McConnell and Servaes, 1990; Hermalin and Weisbach, 1991). This is supported by evidence from studies that find a positive relationship between stock ownership and performance including (Claessens et al., 2002; Gompers et al., 2003; Bozec and Laurin, 2008). However, at higher levels of ownership concentration, dominant shareholders may be more risk-averse and, more importantly, they can become entrenched and effort-averse, which may have a detrimental effect on performance (Morck et al., 1988; Cho, 1998; Gompers et al., 2003), suggesting the presence of an optimal ownership proportion.

Furthermore, Bagnani et al. notes a complex variable impact on bondholder returns (1994), finding that performance is influenced by various ownership forms. This indicates that while high board stock ownership can be beneficial, the overall impact of ownership structures on firm performance is complex and context-dependent.

Individual blockholder ownership is calculated by classifying a board member as a blockholder if their ownership surpasses 4.5% of the company's stock. This threshold is significant as most countries, including the USA, which requires public disclosure of ownership at this level (Edmans and Holderness, 2017). In the context of S&P 500 companies, this ownership threshold invariably represents a substantial asset value.

2.1.4 CEO / Chair separation

Chief Executive Officers whom are also employed as the Board Chairman, otherwise known as *CEO duality* sparks debate about its effect on firm performance, involving contrasting views and mixed empirical evidence. This research posits that CEO duality adversely impacts firm performance, a standpoint aligning with the Agency Theory framework (Fama and Jensen, 1983; Jensen, 1993) and supported by empirical studies including (Duru et al., 2016; Daily and Dalton, 1994; Coles et al., 2001; Rechner and Dalton, 1991) that find statistically negative impacts on firm performance. This signals the potential for reduced board oversight and increased managerial entrenchment when the roles of CEO and board chair are combined. This theoretical perspective is grounded in the belief that duality consolidates power in the hands of a single individual, thereby compromising the board's ability to effectively monitor and evaluate executive decisions, a critical function for ensuring shareholder interests (Jensen and Meckling, 1979).

It is important to mention how empirical research has also yielded inconclusive results, with other studies suggesting that duality can enhance firm performance by providing unified leadership that is agile and effective in dynamic markets (Donaldson and Davis, 1991; Salancik and Pfeffer, 1978). This ambiguity is partly attributed to the difficulty in establishing a causal relationship due to endogeneity issues, which is addressed in section 2.2.

The passage of the Sarbanes-Oxley Act (Act, 2002) aimed at enhancing corporate governance and accountability, underscores the regulatory and scholarly concern regarding the implications of duality for firm governance. Furthermore, the activism against CEO duality by shareholders of prominent firms such as News Corp, JP Morgan Chase, and Goldman Sachs highlights the growing unease among investors about the potential conflicts of interest and governance challenges posed by this structure (Munsif and Singhvi, 2022).

2.1.5 Board Diversity

Board diversity can be defined as the heterogeneity among the members of boards in terms of age, gender, ethnicity, nationality, education, and experience. It has gained considerable academic, political, and media attention at both national and global levels in recent years (Bassyouny et al., 2020; Cordeiro et al., 2020). In today's business environment it is essential for organisations to maintain greater diversity within their boards, to enhance perspectives and competencies (Khatib et al., 2021).

The prevalence of women on boards is the most frequently analysed metric for evaluating board diversity, with several studies having explored its relationship with firm performance. These reports showcase positive associations between the presence of women and diversity in general on US boards with firm performance, measured by Tobin's Q, ROA, and ROE (Carter et al., 2003; Erhardt et al., 2003). Similarly, in Spain, a country noted for its low female executive presence, it has been observed that female board members significantly enhance firm value (Campbell et al., 2008). Conversely, Martinex-Jimenez et al, reports a positive, but not statistically significant, link between gender diversity and performance (2020). Later work from Carter et al. and Garanina and Kaikova found no discernible impact of gender diversity on financial outcomes in US boards (2010; 2016), suggesting diverse impacts of gender diversity on firm dynamics across different contexts and measures.

Most previous research has focused on gender as a key measure of board diversity, with less attention given to other dimensions (Khatib et al., 2021), particularly ethnicity. A study by Marimuthu finds a positive correlation between ethnic diversity and firm performance 2008, whilst Tariah finds inconclusive evidence for such a relationship 2019. Consequently, this MCDA will take the view that increased gender and ethnic diversity improves performance, inline with the relevant prior research highlighted.

2.1.6 Voting type

This research assumes that dual class voting structures, which distinguish between Class A shares (with more voting power typically held by founders and initial investors) and Class B shares (issued during IPOs to later investors), negatively affect firm performance. This assumption is rooted in Agency Theory (Fama, 1980), which suggests that dual class voting systems can exacerbate conflicts of interest between shareholders and management. This leads to decisions that may not align with the broader interests of all shareholders, thereby potentially diminishing firm performance. On the other hand, Stewardship Theory (Davis et al., 2018) argues that dual class shares can enhance performance by facilitating more unified and visionary leadership. This stance is further informed by findings from (Nüesch, 2016), indicating that dual class shares might only be beneficial in contexts where firms require external financing. This view acknowledges the challenges of endogeneity in corporate governance research, which make causal inferences difficult (Larcker et al., 2011; Adams and Ferreira, 2008; Bennedsen and Nielsen, 2010).

2.1.7 Tobin's Q

Tobin's Q ratio was used as the performance metric for this research as it is widely accepted as a strong measure of firm performance (Anderson et al., 2004), which effectively captures the market's valuation of a company relative to its assets. Unlike accounting-based measures, such as market capitalisation, which do not fully reflect the market's expectations about a firm's growth prospects, Tobin's Q offers a well rounded perspective by comparing the market value of a firm's equity and debt to the replacement cost of its assets (Tobin, 1969; Lindenberg and Ross, 1981). Furthermore, research has demonstrated that Tobin's Q is a significant predictor of future investment opportunities and firm performance, making it a valuable tool for analysts and researchers to gauge a company's growth and value creation capabilities (Chung and Pruitt, 1994; Perfect and Wiles, 1994).

2.2 Other considerations

Several other corporate governance variables were considered to be included in the dataset, including CEO compensation, average tenure, CEO education, meeting frequency and meeting attendance. Unfortunately, these variables diverge from the structural focus on the board of directors. Additionally, their high annual volatility would introduce significant noise into the dataset, complicating the analysis and obscuring clear conclusions.

Within corporate finance research, experts can often overlook sources of endogeneity, notably how a company's current management practices might be shaped by its past performance (Lin et al., 2019). Given that real-world examples of clear-cut evidence are scarce, ignoring this link can skew findings because researchers are led to use historical data sources. This approach unrealistically assumes that present management decisions are not influenced by past company outcomes, a simplification that may undermine the reliability of their conclusions. From a general perspective, the research of this dissertation will reduce endogeneity by including time-series data within the Cluster Analysis and the MCDA, notably from 2007, which was the earliest available data.

Chapter 3

Research

3.1 Data Collection & Preprocessing

All data for this project was collected from Wharton Research Data Services (WRDS) through the University of Edinburgh subscription. Data from three providers, BoardEx, Compustat and ISS ESG was used. The data was collected through the WRDS API and accessed using the 'wrds' python library. Individual SQL queries to the databases were made, filtering for the S&P500 ticker symbol's and correct dates required.

Python scripts were created to pull the variables off the databases and perform the necessary preprocessing steps before merging them together using Pandas. The exact variables and calculations are provided in the data dictionary in Table 3.1.

Standard and Poor's 500 (S&P500) index includes the largest 500 publicly traded companies in the United States as measured by market capitalisation. This dissertation focuses on these companies for multiple reasons. Firstly, they have a major influence in the national US and global economy, often viewed as leaders in their respective industries. Secondly, analysing this index makes this dissertation increasingly relevant in the eye of investors, who tend to invest into companies included in this index. Additionally, companies within this index are subject to more rigorous and standardized reporting requirements, making data on their corporate governance practices more accessible and comparable, enhancing the reliability of the findings.

The list of S&P500 companies was collected from $CRSPIndexes$, $dailys\&p500$ table, which contained the join and exit dates of companies from the index. The other preprocessing steps for the individual variables were as follows.

Metric	**Provider, Library.Table, Variable)**	**Calculation**
Board Size	ISS ESG, risk.rmdirectors	Count per Ticker
%INEDS	ISS ESG, risk.rmdirectors, 'CLASSIFICATION'	$if classification == ['I-NED', 'I', 'NI-NED']$
Board Ownership %	ISS ESG risk.rmdirectors, 'NUM OF SHARES'	$\frac{sharesoutstanding}{sum(numshares)}$
Blockholders	ISS ESG risk.rmdirectors, 'NUM OF SHARES'	$\frac{totaloutstandingshares}{\sum(directorshares)} * 100 > 4.5$
CEO Dual	ISS ESG, risk.rmdirectors 'Employment-CEO' & 'Employment-Chairman'	Dual $if both == 'Yes'$
Gender Ratio	BoardEx boardex.na-wrds-org-summary, 'GenderRatio'	N/A
Ethnic Ratio	BoardEx boardex.na-wrds-org-summary, 'NationalityMix'	N/A
Dual class	ISS governance 'Dualclass'	N/A
Vote Power	ISS ESG risk.rmdirectors, 'PCNT CTRL VOTING POWER'	$if val \geq 0$

Table 3.1: Board Structure Data Dictionary

Tobin's Q value was calculated using the equation in Figure 3.1. Total market value 'mkvalt' from Compustat's 'Fundamentals Annual' database was used for the numerator of $EquitiesMarketValue + LiabilitiesMarketValue$. Total assets 'AT', was used from the same database for the denominator of $EquityBookValue + LiabilitiesBookValue$ as for publicly traded companies, book value is equal to asset value.

$$\text{Tobin's q} = \frac{(\text{Equity Market Value} + \text{Liabilities Market Value})}{(\text{Equity Book Value} + \text{Liabilities Book Value})}$$

Figure 3.1: Tobin's Q Ratio Equation

This study uses Spearman's Rank correlation coefficient to examine the relationships with Tobin's Q. This coefficient assesses the monotonic relationship between two variables, instead of the linear relationship. It was chosen over alternatives like Pearson's correlation coefficient due to it's reduced sensitivity to outliers, and its ability to effectively analyse relationships without the prerequisite of linear correlation. Spearman's Rank is also well-suited to the complexities of this dataset. This was the equation used, where the raw scores X_i, Y_i are converted to ranks $R(X_i), R(Y_i)$.

$$r_s = \rho_{R(X),R(Y)} = \frac{cov(R(X),R(Y))}{\sigma_{R(X)}\sigma_{R(Y)}}$$

ρ denotes the Pearson correlation coefficient, applied to the rank variables.
$cov(R(X),R(Y))$ is the covariance of the rank variables.
$\sigma_{R(X)}$ and $\sigma_{R(Y)}$ are the standard deviations of the rank variables.

3.2 Data Pipeline

The first objective of this project was to establish a data pipeline to analyse the structure of corporate governance boards. For this, Apache Airflow was used, which is a workflow management platform for data engineering pipelines. Airflow's compatibility with Python allowed for the easy incorporation of various python libraries, files and classes. The Airflow pipeline used was created by Yong Chen. This enabled dataset creation, score generation and clustering to be performed using Extraction, Transformation, and Loading (ETL) processes and Directed Acyclic Graphs (DAGs), to the latest data, keeping the analysis current and relevant.

3.3 Multi-Criteria Decision Analysis

MCDA stands for Multi-Criteria Decision Analysis, it is a statistical method to structure complex decision-making problems, involving multiple variables or criteria. It was chosen to provide direct comparison between companies by ranking them through a single score based on the strength of their board structure.

3.3.1 Methodology

The objective of using a MCDA method is to primarily address the shortcomings and inconsistencies found in conventional corporate governance indices and to examine whether this new approach can uncover meaningful insights regarding company performance through regression analyses.

There have been calls to move beyond multiple regression techniques within corporate governance analysis (Woodside, 2014). As highlighted within a comprehensive literature review, (Behzadian et al., 2010; Mareschal, 2015), there is only a singular study that uses an MCDA approach to compare performance with a wide range of corporate governance factors (Guney et al., 2020).

This dissertation is different from Guney et al's research in the methodology, timeframe, the scope of firms analyzed, and the focus of governance variables. Where Guney et al employs PROMETHEE methods, combined with AHP weighting for MCDA, this research adopts the TOPSIS method and integrates a weighting approach which merges expert prior research with linear regression analyses. In temporal scope, Guney et al's work spans from 2002 to 2014, whereas this dissertation extends its analysis from 2007 to 2024, thus capturing more recent trends and changes. Furthermore, while Guney et al's study encompasses a generalized set of public US firms, this investigation narrows its scope to strictly S&P 500 companies. Finally, Guney et al's research takes a broader view of governance variables, whereas this study focuses on board structure characteristics related to firm performance.

3.3.2 TOPSIS Method

The TOPSIS method (Tzeng and Huang, 2011) was used for this MCDA, which identifies the best option from a set of alternatives based on their proximity to the best and worst solutions. This is achieved by calculating the geometric distance of each alternative to the best and worst points in the criteria space. An overview of this process is provided in the steps below:

1. Create an evaluation matrix consisting of m alternatives and n criteria, with the intersection of each alternative and criteria given as $(X_{ij})_{m*n}$.

2. The matrix $(X_{ij})_{m*n}$ is then normalised to form the matrix $R = (r_{ij})_{m*n}$ using a linear normalisation method.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}$$

   Where $i = 1,2,...,m, j = 1,2,...,n$

3. Multiply this matrix by the weights: $t_{ij} = r_{ij} * w_j$

4. Determine the worst alternative A_w and the best alternative A_b:

$$A_w = max(t_{ij}|i = 1,2,...,m)|j\varepsilon J_-, min(t_{ij}|i = 1,2,...,m)|j\varepsilon J_+ \equiv t_{wj}|j = 1,2,...,n$$

$$A_b = min(t_{ij}|i = 1,2,...,m)|j\varepsilon J_-, max(t_{ij}|i = 1,2,...,m)|j\varepsilon J_+ \equiv t_{bj}|j = 1,2,...,n$$

   Where $J_+ = j = 1,2,...,n|j$ is associated with the criteria having a positive impact, and Where $J_- = j = 1,2,...,n|j$ is associated with the criteria having a negative impact.

5. Calculate the L^2 distance between the target alternative i and the worst condition A_w

$$d_{iw} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{wj})^2}$$

   Where $i = 1,2,...,m$

and the distance between the alternative i and the best condition A_b

$$d_{ib} = \sqrt{\sum_{j=1}^{n}(t_{ij} - t_{bj})^2}$$

Where $i = 1, 2, ..., m$, d_{iw} and d_{ib} are L^2-norm distance from the target alternative i to the worst and best conditions, respectively.

6. Calculate the similarity to the worst condition: $s_{iw} = d_{iw}/(diw + d_{ib}), 0 \leq s_{iw} \leq 1, i = 1, 2, ..., m$.

3.3.3 Weights

As mentioned in section 2.1, linear regressions are the most widely used statistical method when analysing corporate governance characteristics in relation to performance.

This research uses linear regressions as well as prior research of individual variables to inform the MCDA weights. Performing linear regressions help to understand the direct impacts of each variable on firm performance for this dataset. It is especially useful where there is limited previous literature regarding its impact within a similar context of S&P500 companies between the years of 2007-2024. This weighting method will ensure a robust and data-driven research approach.

Variable	Normalised Weight	Impact
Board Size Mean	0.11	-
%INEDs	0.14	+
Board Ownership	0.03	+
Blockholders	0.03	+
CEO Dual	0.05	-
Gender Ratio	0.03	-
Ethnic Ratio	0.33	+
Dual Class	0.17	-
Vote Power	0.11	+

Table 3.2: Variable weights and their impacts used for the MCDA

The weights shown in Table 3.2 are informed from both prior literature and regression analyses. The impact column describes if a higher value for that variable corresponds to an improvement on performance (+) or a diminishment from performance (-), a negative impact will be minimised in the MCDA, whilst a positive impact will be maximised. The rationale for each variable weighting and impact is explained below:

- **Board size**: A Gaussian correlation was observed between board size and Tobin's Q, suggesting that the mean value observed is the optimal board size. Therefore, this column's values were transformed to show the distance from the mean, displaying a negative linear correlation, as further from the mean implies a less desirable board size. MCDA can only maximise or minimise variables, therefore this linear transformation is required. The 'Board size mean' was assigned a moderate, negative weight of 0.11, in the analysis due to its complex impact on firm performance, and relationship with industry specific trends.

- **Independent Non-Executive directors**: The proportion of independent non-executive directors was given a larger weight of 0.14, with a positive impact. This is because, as noted in the literature, there is a positive correlation with performance, aligning with Agency Theory and Resource Dependency Theory. This emphasises the potential to mitigate agency problems and contribute valuable resources.
- **Board stock ownership**: The proportion of stock owned by the board is represented by ’Board Ownership’ and the number of blockholders, who are directors owning over 4.5% of their company’s stock is represented by ’Blockholders’. Both of these variables have been assigned a lower weight of 0.03 because while previous studies generally indicate a positive effect, no significant correlation to Tobin’s Q is found in regression analysis on this dataset.
- **CEO / Chair separation**: CEO duality was also assigned a low weight of 0.05, with negative impact, to reflect its ambiguous impact on performance as it is a highly debated and context-dependent topic, with many studies leading to inconclusive results.
- **Board Diversity**: The proportion of male directors represented by ’Gender ratio’ was given a low, negative weight of 0.03. As, whilst prior literature mostly indicates a positive correlation with performance, this dataset does not support that finding and instead suggests minimal or no correlation. The proportion of ethnic minorities on the board is represented by ’Ethnic ratio’. This was assigned a much larger weight of 0.33, with positive impact because, unlike the gender ratio, this dataset shows a strong positive correlation between ethnic diversity and performance, in line with previous research.
- **Voting type**: Dual class voting was assigned a moderate weight of 0.17, with negative impact. This negative relationship with performance is due to exacerbated conflicts of interest, as suggested by Agency Theory. Conversely, proportionate voting was assigned a positive weight of 0.11 as a high percentage of voting directors has been found to foster an alignment of interests and diversity of opinions, thus improving performance.

3.3.4 MCDA Results

The TOPSIS score created for each company was normalised from zero to one and allowed for a direct comparison between companies, thus leading to a ranking system shown in Table 3.3.

Rank	TOPSIS Score
1.0	0.965231
2.0	0.951843
3.0	0.941936
4.0	0.922942
5.0	0.912377
...	...
496.0	0.503406
497.0	0.500135
498.0	0.463013
499.0	0.430927
500.0	0.402342

[498 rows x 10 columns]

Table 3.3: Visualisation of how companies can be ranked on their TOPSIS scores, where each row in the table is a company.

The scatter plot of the TOPSIS scores and Tobin's Q values are shown in Figure 3.2

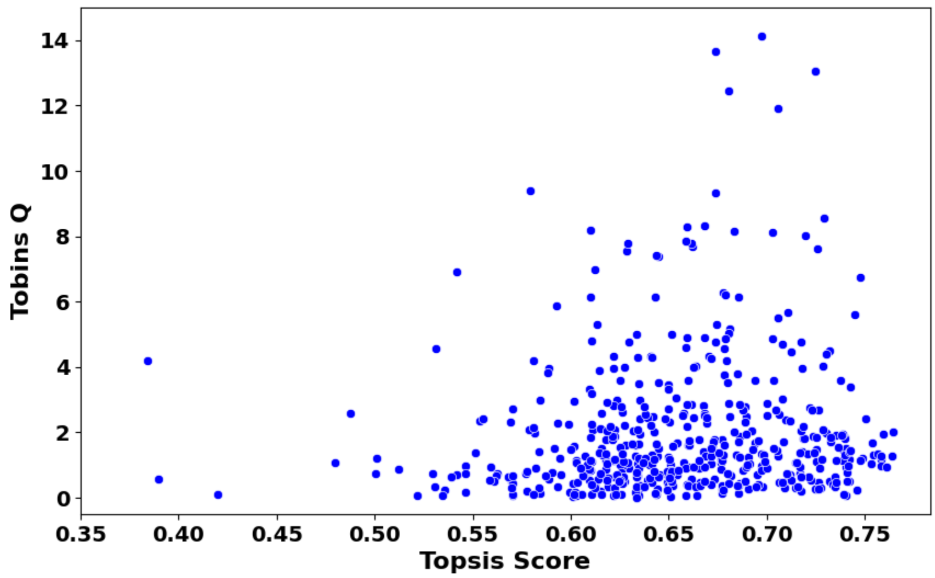

Figure 3.2: Scatter plot of TOPSIS score against Tobin's Q value

The results of the graph show a significant portion of the data points are concentrated within a Tobin's Q score of zero to three. Additionally, analyzing outliers can offer insights into companies that have high Tobin's Q values, which reach up to 14, regardless of their TOPSIS scores. These anomalies could represent high-growth companies that have gained large investor interest, possibly reflecting sectors in a speculative bubble as such energy, semiconductors or artificial intelligence for 2023.

The analysis also finds a mild positive, non-linear correlation of 0.145, using a Spearman's Rank correlation coefficient between the TOPSIS score and Tobin's Q. This weak correlation highlights the intricate and often indirect interactions between company performance and market expectations, suggesting that the relationship between the TOPSIS score and Tobin's Q may be more complex than initially anticipated. To address this challenge, Cluster and Factor Analyses will be performed, aiming to uncover similar groups and latent variables driving performance.

Sensitivity Testing

To ensure these results were reliable and help quantify uncertainty, sensitivity testing was performed on the results. This involved changing the weights individually from a minimum value of 0.1 up to maximum value of 0.99 in increments of 0.1. The differences between maximum and minimum TOPSIS scores created with the varied weights were calculated and are displayed in Table 3.4:

Variable	Sensitivity Score
Board Size Mean	0.000068
%INEDs	0.0002
Board Ownership	0.003
Blockholders	0.0001
CEO Dual	0.0004
Gender Ratio	0.00003
Ethnic Ratio	0.00007
Dual Class	0.0002
Vote Power	0.0005

Table 3.4: Results from sensitivity testing. This table displays the differences between maximum and minimum TOPSIS scores, when weight is varied from 0.1-0.99.

The small variations prove the resilience of the MCDA to modifications in individual weights, showcasing its dependability as a methodological framework in corporate governance research. This emphasises that the derived governance score is the result of the interactions among multiple variables, rather than being dominated by any single variable.

2007-2023 Analysis

By averaging the past three years' governance variables for each company, our approach enriches the TOPSIS scores and trains the MCDA model with a historical perspective. This method demonstrates the robustness and stability of the MCDA, by showing a stable output over time as well as addressing endogeneity within the dataset, enhancing the credibility of our findings. The results are visually represented in Figure 3.3.

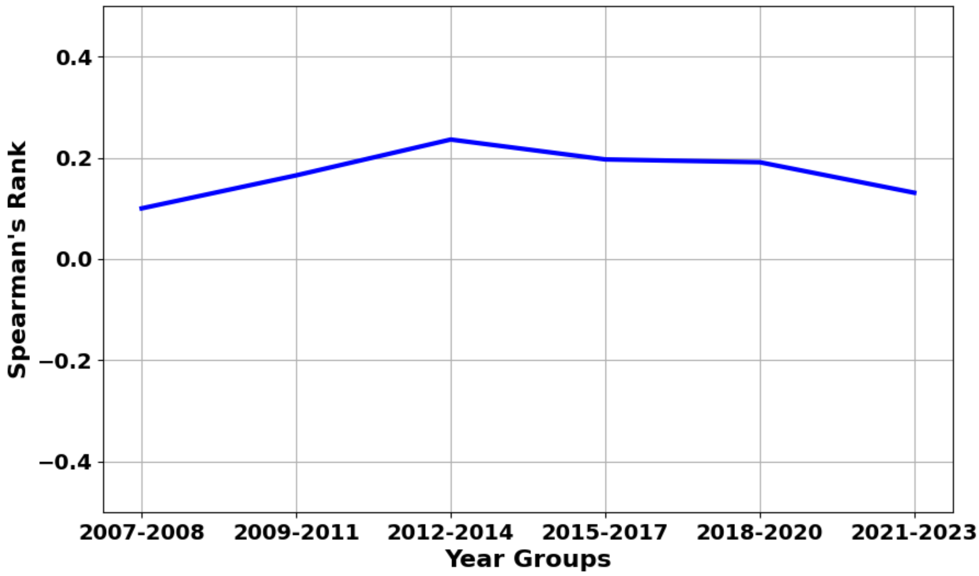

Figure 3.3: Spearman's Rank correlation over time, using MCDA scores calculated over 3 years

The two graphs below depict the results from 2015 through to 2017 in Figure 3.4 and 2018 through to 2020 in Figure 3.5.

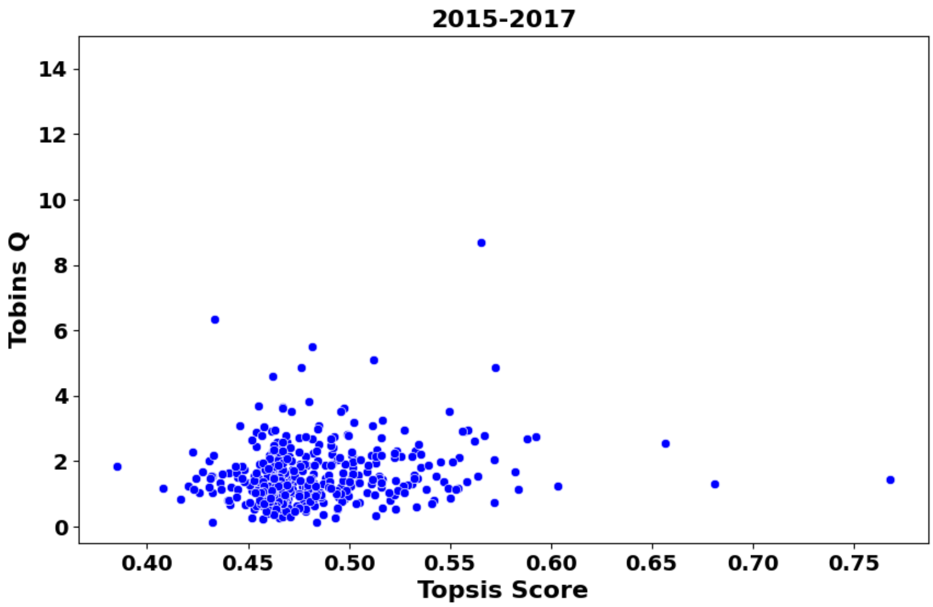

Figure 3.4: Scatter plot representing TOPSIS score against Tobin's Q for years 2015-2017

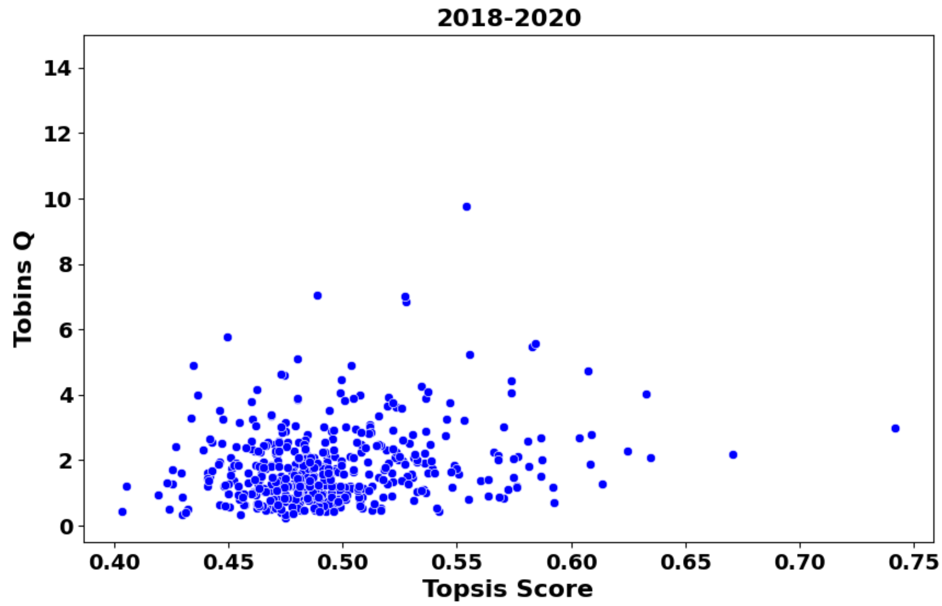

Figure 3.5: Scatter plot representing TOPSIS score against Tobin's Q for years 2018-2020

3.4 Cluster Analysis

Cluster Analysis is a well-known exploratory data analysis technique. It performs the task of grouping a set of objects, in this case, companies together in such a way that companies in the same cluster are more similar to each other than to ones in other clusters. There are different types of algorithms that can perform Cluster Analysis, among the most popular is the K-Means algorithm, which is used for this analysis.

Cluster Analysis was performed to deepen our understanding of how the specific characteristics of different governance structures impact performance within our dataset. It provides a much greater depth of understanding to the dataset, when combined together with Factor Analysis, complimenting the MCDA.

3.4.1 Methodology

K-Means

The Cluster Analysis aims to identify groups of companies based of the nine variables being analysed. The K-Means algorithm uses Euclidean distance to assess the similarity between data points (Lloyd, 1982), and was chosen due to its efficiency and scalability to the large dataset. K-Means assumes that the clusters are somewhat circular in shape, where each cluster has a centroid value, corresponding to the arithmetic mean of the data points assigned to the cluster.

$$\sum_{i=0}^{n} \min_{\mu_j \varepsilon C}(||x_i - \mu_j||^2)$$

K-Means Equation

To determine the optimal number of clusters, the 'Elbow' method was implemented, which plots the Sum of Squared Errors (SSE) against the number of clusters. SSE is a measure of how close each point in a cluster is to the centroid of that cluster, therefore representing the tightness of clustering. This method avoids overfitting the dataset, whilst still obtaining well-defined clusters.

K-Means clustering is sensitive to outliers in the dataset, which can skew clustering. To mitigate this issue, Principal Component Analysis (PCA) was implemented so that outliers can be ignored and the clusters can be more accurate. PCA requires a level of variance to be retained when performing the dimensionality reduction.

Considering the clustering's high sensitivity to outliers, we opted to retain 87% of the variance. This value was carefully chosen to balance the trade-off between minimizing the impact of outliers and preserving the integrity of the data.

To check how well fitted the clusters are, the 'Silhouette score' was calculated using the equation below. This score ranges from -1 to 1, where a score of 1 indicates perfect distinct clusters and -1 represents no clusters present. This analysis produced a score of 0.62, showing a strong fit, confirming the clusters are both meaningful and well-defined.

$$SilhouetteScore = \frac{(b_i - a_i)}{max(a_i, b_i)}$$

Silhouette Score Equation

For every data point, a_i is the average distance to other data points within that cluster, and b_i is the average distance to all other clusters it is not part of. The average of these scores is taken to obtain the overall score.

Scikit's sklearn.cluster machine learning python package was used to perform the K-Means clustering and the sklearn.decomposition package was used for the PCA (Scikit-Learn Developers, 2007).

Time-Series Clustering

To account for the longitudinal nature of the data, a time-series, distance-based clustering technique was also implemented. Similar to K-Means, the datasets undergo preprocessing with Principal Component Analysis (PCA) prior to clustering, to reduce dimensionality and highlight the most significant features.

The technique used is called Dynamic Time Warping (DTW) and is calculated as the squared root of the sum of squared distances between each element in X and its nearest point in Y. This algorithm finds the optimal non-linear alignment between two time-series. This technique is preferred over Euclidean distance for time-series Cluster Analysis because it can handle variations in speed and alignment in the data, effectively matching sequences that are similar in shape but may occur at different times or speeds. A Euclidean distance measurement however, cannot handle data variations and would instead skew the results. The DTW equation is from (Sakoe and Chiba, 1978) and implemented as follows by (Tavenard et al., 2020) in tslearn's clustering package.

$$DTW(x,y) = min_{\pi} \sqrt{\sum_{(i,j)\varepsilon\pi} d(x_i, y_j)^2}$$

where $\pi = [\pi_0, ..., \pi_K]$ is a path that satisfies the following properties:

- it is a list of index pairs $\pi_k = (i_k, j_k)$ with $0 \leq i_k < n$ and $0 \leq j_k < m$
- $\pi_0 = (0,0)$ and $\pi_k = (n-1, m-1)$
- for all $k > 0, \pi_k = (i_k, j_k)$ is related to $\pi_{k-1} = (i_{k-1}, j_{k-1})$ as follows:
  - $i_{k-1} \leq i_k \leq i_{k-1} + 1$
  - $j_{k-1} \leq j_k \leq j_{k-1} + 1$

3.4.2 Cluster Analysis Results

K-Means

The graph below illustrates the Elbow method, a technique used to determine the optimal number of clusters for data segmentation. The 'elbow' point on the graph, where the slope sharply flattens, mimicking the bend of an elbow. In Figure 3.6, this point occurs at $x = 3$ clusters, indicating that increasing the number of clusters beyond this does not significantly enhance the explained variance of the data by the clustering.

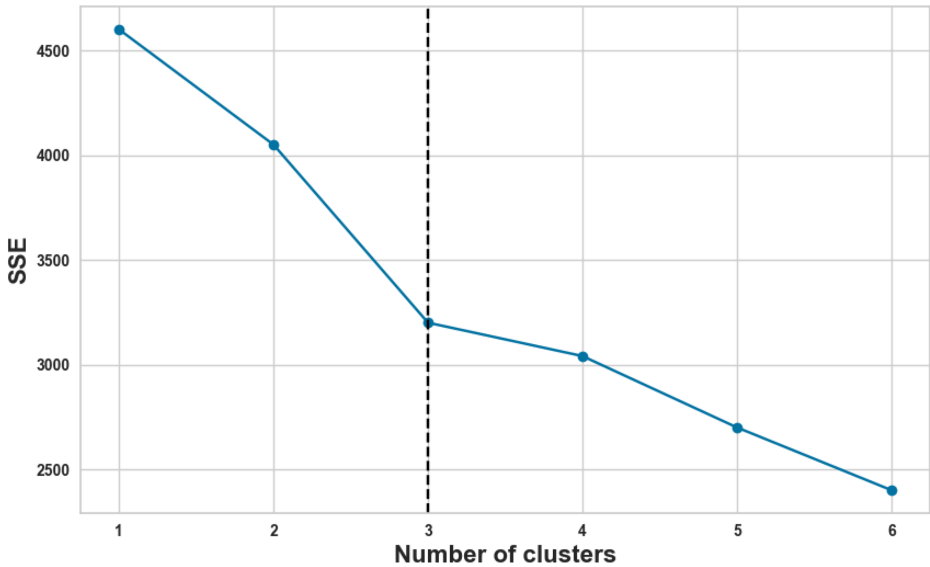

Figure 3.6: Line graph of Sum of Square Errors (SSE) against Number of Clusters. Used to determine the optimal number of clusters, represented by the 'elbow' at x=3

The magnitude graph in Figure 3.7 indicates that clusters 0 and 2 exhibit a greater variable differences, as evidenced by a much greater magnitude of all points from the centroid values. The graph on the left quantifies the distribution of data points across each cluster, revealing that clusters 0 and 2 house a comparably high number of companies, as well as greater magnitude, indicative of high dispersion, by displaying a strong positive correlation.

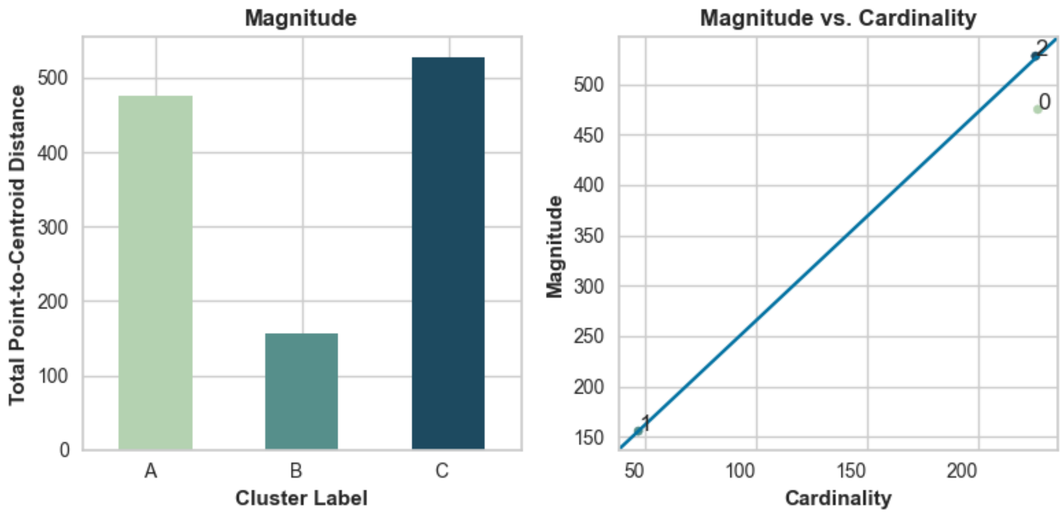

Figure 3.7: Left: Bar chart representing Magnitude of Point-To-Centroid Distance. Right: Plot for Magnitude against Cardinality for each cluster, with a line of best fit.

The specific variable deviations from the mean of each cluster are shown in the bar chart in Figure 3.8.

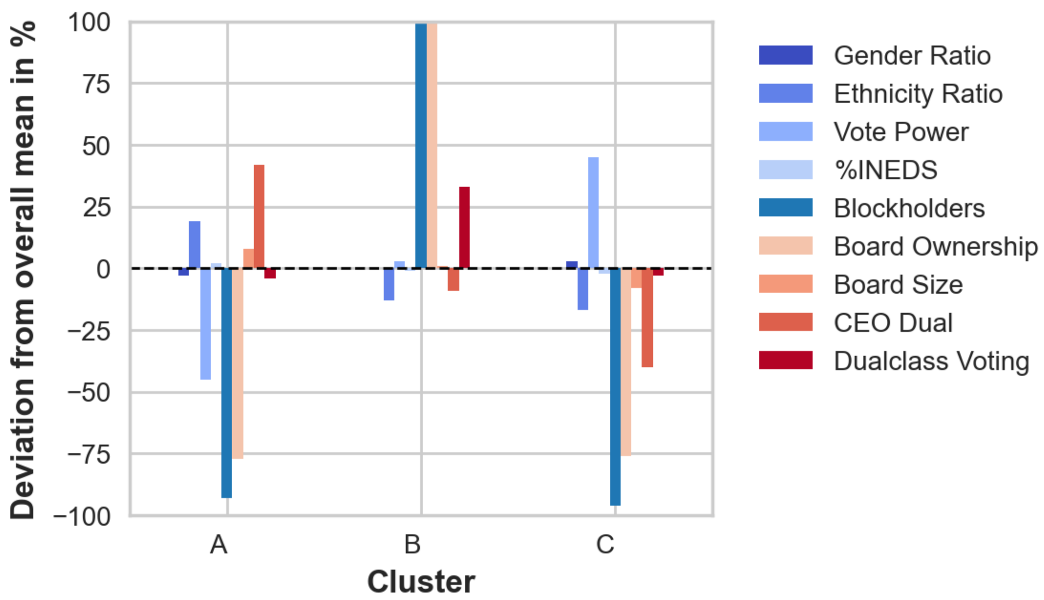

Figure 3.8: Bar chart representing the influence of each variable on the clusters

Cluster A has a higher prevalence of larger boards with less concentrated ownership and voting power, indicating a preference for a more diverse and democratic board structure.

Cluster B is characterized by boards with substantial director ownership, a high number of blockholders, and the presence of dual-class voting. It also has a lower ethnic ratio and a reduced percentage of independent directors. This structure indicates the preference for control retention among a smaller number of individuals. The below-average representation of ethnic minorities and fewer independent directors may raise concerns about governance practises, as this practise is not being widely accepted as a modern organisational management strategy.

Cluster C distinguishes itself with the presence of small boards and a dual CEO structure, yet it features a low proportion of independent directors. Additionally, it has high voting power without dual-class voting and exhibits a high gender diversity ratio but a low ethnic ratio. Despite the seemingly paradoxical aspects of this configuration, it implies a tightly controlled structure which is typical of family-owned or founder-led businesses.

This information is further visualised in a radar plot, as illustrated in Figure 3.9, show-casing the mean values of features for each cluster. The clusters are differentiated using three colors.

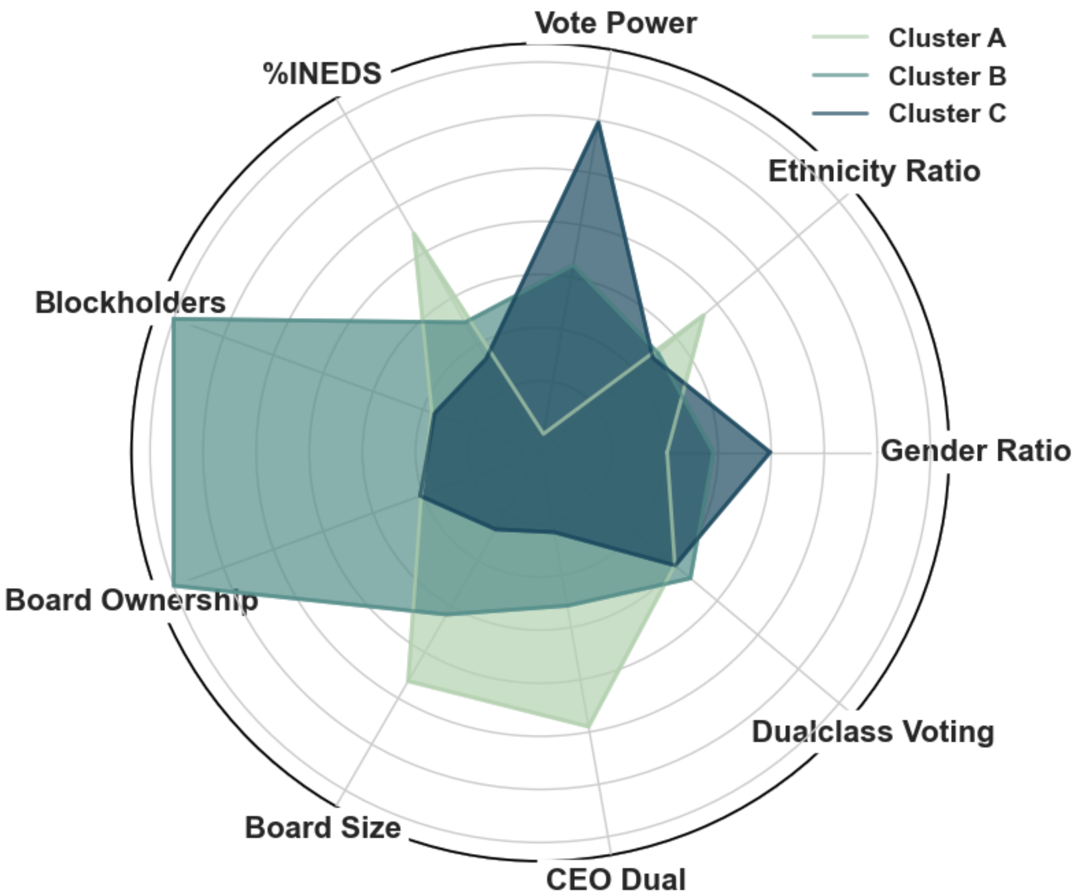

Figure 3.9: Radar Chart representing the influence of each variable on the clusters.

Time-Series

As well as K-Means clustering for the 2023 dataset, previous data was also analysed which required time series k-means clustering to account for the previous data. The results from this clustering technique are shown in Figure 3.10.

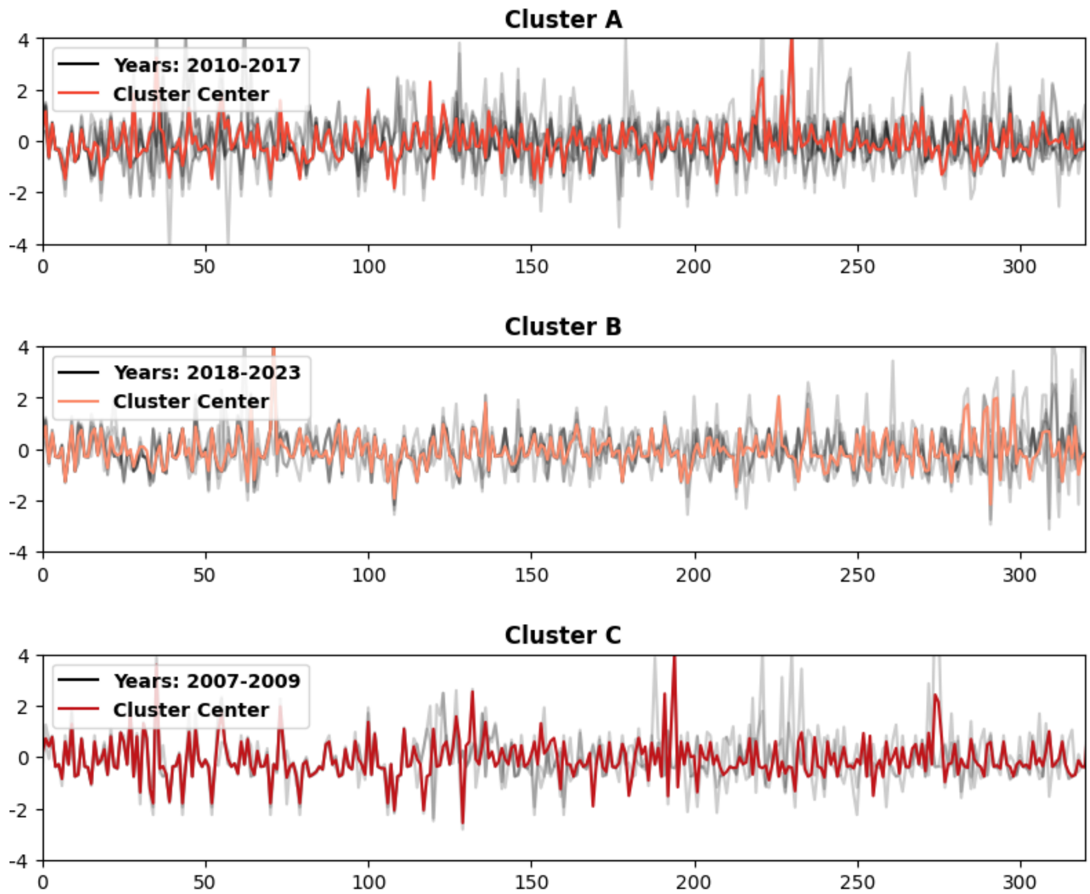

Figure 3.10: 3 graphs representing specific clusters of years created by the time-series clustering. They each show the change in variance over time.

Each graph corresponds to a cluster as labelled. The faded black lines represent the set of time series from the training set that were assigned to the considered cluster. Whilst the red lines represents the cluster centroid. The legend provides information on what time-series data has been assigned to each cluster.

The clusters created correspond to the periods 2007-2009, 2010-2017, and 2018-2023, indicating the gradual industry adaption to improved governance and board structure over time. A closer look at the third cluster reveals a distinctly different pattern from the first two, with some significant fluctuations at the cluster's center. The variance is noticeable, with some time series showing strong deviations from the center, indicating outlier years or companies with significantly different board structures. Additionally, the pattern reflects the impact of the financial crisis of 2007-2008 on board structure strength, indicating dramatic shifts and a potential reassessment of governance practices during and immediately after the crisis.

The first cluster displays some fluctuation, with the cluster center indicating a somewhat stable pattern. The variance around the cluster center remains moderately high, suggesting there is diversity in the evolution of individual board structures over time. The findings suggest a period of transition or diverse approaches towards improving board structure strength.

Finally, the second cluster shows less volatile patterns compared to the first, with the cluster center showing a smoother trend. While variance remains, it is less pronounced than observed in the first cluster, suggesting that approaches to board soundness became more standardised during this period, perhaps converging towards a common standard or best practice. This hypothesis further affirms the importance of training the MCDA model on the latest data to accurately identify the leading companies within corporate governance.

3.5 Factor Analysis

Factor Analysis is a statistical technique that explains the variation among observed, correlated variables through a smaller set of unobserved variables known as factors. In this study, Factor Analysis served as a tool to simplify a complex, multivariate dataset, by reducing its dimensionaility. This approach facilitated the discovery of latent variables and hidden constructs, which were then examined for their impact on performance.

3.5.1 Methodology

Firstly, a Kaiser-Meyer-Olkin (KMO) Test was used to measure the suitability of the dataset for Factor Analysis. KMO estimates the proportion of variance among all the observed variables, where a lower proportion is more suitable. KMO values range between 0 and 1. A value of KMO above 0.6 is considered adequate for Factor Analysis and the dataset achieved a value of 0.68.

Next, Bartlett's Sphericity Test was used to check whether the data is a random sample from a multivariate normal population $MVN(\mu, \Sigma)$ where the covariance matrix Σ is a diagonal matrix. The value of the test statistic is 993.4. Under the null hypothesis, the probability of observing a statistic this large or larger by chance alone is exceedingly small (1.23×10^{-101}). Therefore, the null hypothesis can be rejected, which justifies the application of Factor Analysis to this data.

The exploratory Factor Analysis was conducted using the $factor - analyser$ python package. The Kaiser criterion approach was used to reduce the set of nine variables to three factors. This method involves observing the Eigenvalues after fitting a model with a number of factors equal to the total number of variables, which in this case was nine. According to the criterion, the number of eigenvalues greater than 1 should be the number of factors, as a value above one indicates that the factor explains more variance than a single observed variable, justifying its inclusion in the model. The results from the Kaiser Criterion approach are as follows

```
Eigenvalues = [1.77400185, 1.56850703, 1.30581012, 1.03055325,
```

```
0.97235837, 0.83666135, 0.67827907, 0.58580841, 0.24802056]
```

As shown, four values are greater than 1, explaining above a singular variable's worth of variance. Therefore, four factors were chosen to be created. This is a widely adopted method which helps to prevent over or underfitting of Factor Analysis models. Finally, an orthogonal rotation was used to achieve a simpler, more interpretable structure in the data. The rotation works by aiming to maximise the variance of the squared loadings of a factor on all the variables in a factor loading matrix, assuming that factors are orthogonal to each other.

3.5.2 Factor Analysis Results

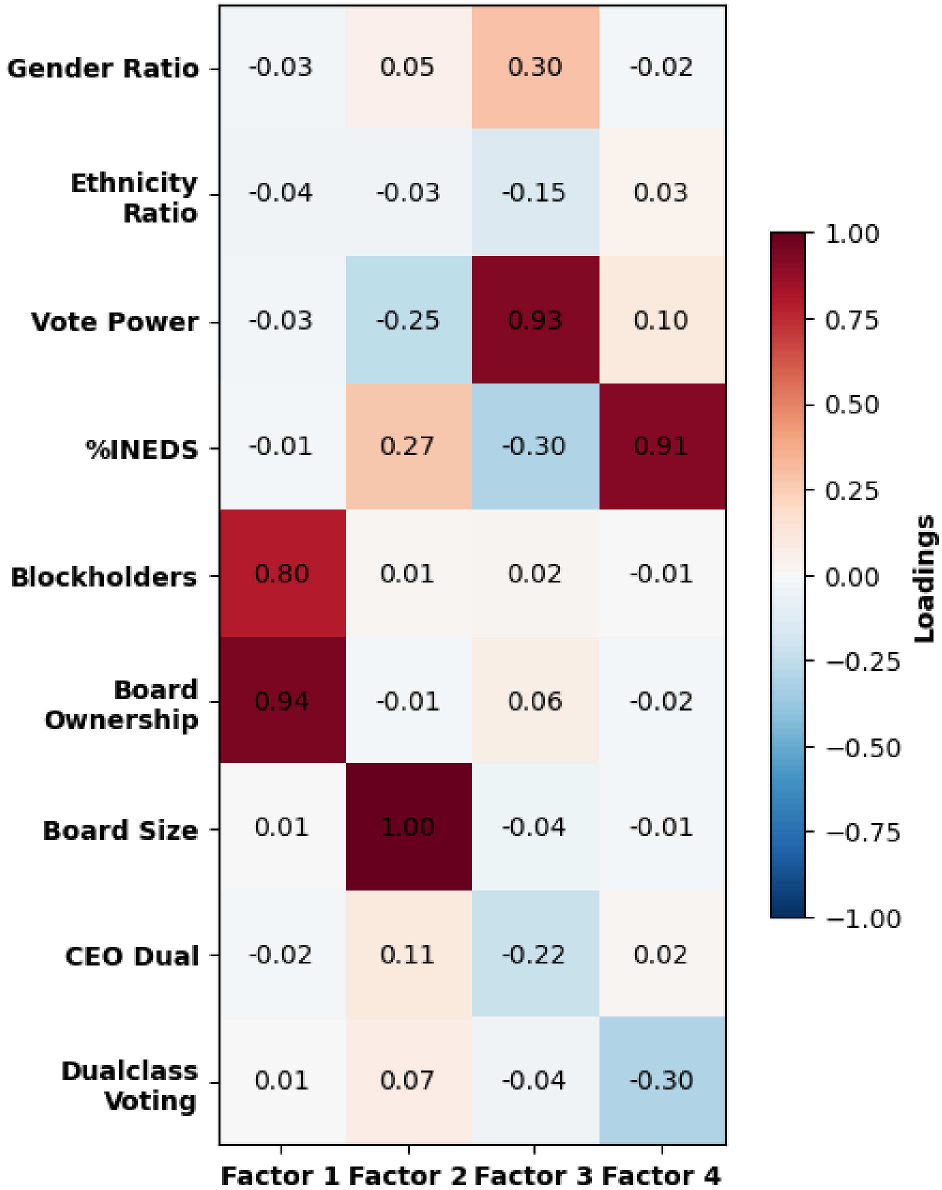

Figure 3.11: Heatmap representing the factor loadings for all 9 variables, mapped onto 4 factors. Red represents positive loadings and blue represents negative loadings.

The heatmap in Figure 3.11 represents a Factor Analysis with a Varimax rotation. Each cell in the heatmap represents the loading of each variable onto the corresponding factor on the x-axis, with the colour intensity indicating the strength and direction of the relationship, with red for positive loading and blue for a negative loading.

Factor 1 is significantly impacted by the proportion of directors with substantial ownership stakes, as well as the overall ownership held by the board. This suggests that the board members are not only experienced but are also deeply invested in the company's success, because they have a vested interest in the firm's value to increase their own wealth. Typically, shares are awarded as part of long-term compensation schemes or may indicate the presence of company founders on the board, further highlighting their commitment and insight into the company's operations.

Factor 2 is strongly associated with board size, where the preference for larger boards is often associated with a broader range of expertise and viewpoints, which can enhance decision-making quality and oversight. Additionally, larger boards tend to feature a higher number of independent directors, as confirmed by the loading of 0.27. There is also evidence of an inclination towards less voting power and a slight preferences for dual CEOs, both of which are frequently interconnected.

Factor 3 shows a high percentage of male directors, substantial voting power, fewer ethnic minorities, and a lower proportion of independent directors. This model emphasises the advantages of centralised control but overlooks the benefits of diversity, which can stifle innovation.

Factor 4 is distinguished by high positive loadings on the proportion of independent directors and negative loadings on dual-class voting systems, where Class A shareholders wield significantly more voting power during polls. This suggests that these companies prioritise independent oversight and equitable shareholder representation, aiming to reduce conflicts of interest.

The factors were compared against Tobin's Q in an attempt to abstract away some complexity from the dataset. This approach has revealed some interesting correlations, visually presented in Figure 3.12 and individually measured by Spearman's Rank. The following chapter delves into further analyses.

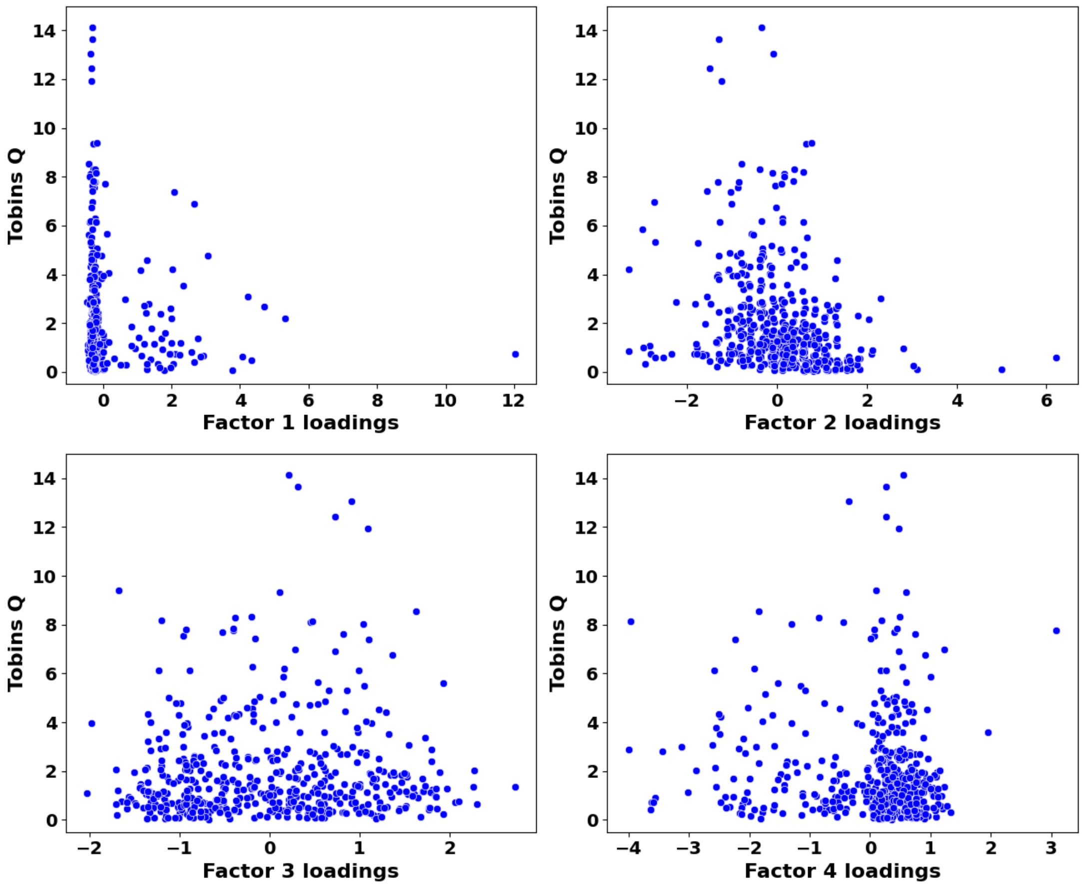

Figure 3.12: 4 Scatter plots of the factors' loadings against Tobin's Q value. The following Spearman's Rank Correlation coefficients with Tobin's Q were calculated. Top left: Factor 1 = -0.1161, Top Right: Factor 2 = -0.4643, Bottom Left: Factor 3 = 0.1058, Bottom Right: Factor 4 = -0.115

Chapter 4

Discussion

4.1 Research Objective 1: Develop a data pipeline to collect, preprocess and analyse corporate governance data

This is the project's Github repository link [1]. The repository contains a README.md file containing set up instructions and required dependencies to run the python scripts. A brief description of each file's purpose is given below:

The datasets are generated using scripts in the Data Creation folder. It outputs the data in a CSV format to a newly created folder, ready for analysis. A visualisation of the final dataset is provided below for further insight.

Board Size	INED %	Board Ownership	Blockholders	CEO Dual	Gender Ratio	Ethnic Ratio	Dual class	Vote Power	Tobins Q
22	90.9	0.174	0.0	0	0.727	0.3	0	31.8	2.805
27	92.6	0.724	0.0	1	0.800	0.0	0	63.0	0.142
19	89.5	0.343	0.0	1	0.700	0.2	0	21.1	0.295
18	88.9	0.112	0.0	0	0.667	0.0	0	22.2	7.550
22	90.9	0.074	0.0	1	0.727	0.0	0	18.2	2.031
...	...	...	...	...	...	...	...	...	...
8	75.0	28.65	3.0	1	0.667	0.0	1	37.5	4.207
24	91.7	0.841	0.0	1	0.615	0.0	0	16.7	2.607
26	92.3	5.446	0.0	0	0.769	0.0	0	80.8	0.470
19	89.5	0.024	0.0	1	0.500	0.4	1	0.0	3.969
24	91.7	0.420	0.0	1	0.667	0.4	0	41.7	9.335

[498 rows x 10 columns]

Table 4.1: A visualisation of the raw dataset used for analyses in this research

[1] `https://github.com/TobyWhittome/BoardDiversity_WRDS`

The analytical framework comprises a comprehensive set of Python scripts designed to facilitate a multi-dimensional analysis. For clustering analysis, the suite includes the folder named 'Clustering'. To explore relationships between variables, the suite features a script, factorAnalysis.py for Factor Analysis, which generates the insightful heatmaps and graphs as presented. The linearRegression.py file performs all the necessary linear regressions.

For the MCDA, the framework provides the MCDA.py file along with a 2 and 3 year average MCDA, for historical analyses purposes. These tools are capable of computing a singular TOPSIS score for each dataset as well as an average Tobin's Q score for companies over the selected period, enabling a detailed correlation analysis.

The data pipeline has been implemented in Airflow, allowing the automation of these scripts to continuously update over time with the latest governance data from the S&P500.

4.2 Research Objective 2: Evaluate the effectiveness of Multi-Criteria Decision Analysis in developing a governance score that can indicate performance.

MCDA was used to assess and score the companies based off the board structure criteria, to aid investors' decision-making processes. To assess the efficacy of the MCDA score as an indicator of performance, two key metrics will be evaluated: its correlation with Tobin's Q and the outcomes of sensitivity analyses.

The weak positive correlation coefficient of 0.145 for the board structure score against Tobin's Q gains importance in the context of other corporate governance studies. Bozec and Bozec provide an exhaustive review of the literature that utilises governance indices to examine the effect of corporate governance quality on firm performance (2012). They observe that the empirical findings linking quality to firm performance in the United States are contradictory, with some finding a positive link, while others find no significant relationship. Brown and Caylor, and Spellman and Watson, find positive relationships between ISS governance provisions, firm performance and GMI rating respectively (2009; 2009). The majority of research on US companies finds no statistical evidence of a positive correlation. For example, Epps and Cereola find no evidence suggesting that the firms' operating performance is related to the firms' ISS corporate governance rating (2008), Daines et al. also finds no correlation between governance ratings and firm performance from ”RiskMetrics” including: The “Corporate Governance Quotient” calculated by RiskMetrics/ISS), GMI (governance quality produced by GovernanceMetrics International), and TCL (a rating produced by The Corporate Library) (2010). More recently, La Torre et al. find little to no correlation with ”ESG Overall” index from CSRHub (2020).

The correlation could also be explained by the argument that companies may be tailoring their governance to their specific needs and strategic goals (Daines et al., 2010). Therefore, assessing their performance solely based on standardised governance ratings might not provide a full picture of how well their governance practices are actually contributing to their success. This complexity and individualisation of governance practices make it challenging to establish a straightforward, one-size-fits-all link between governance ratings and company performance. Given that large commercial organisations, with substantial expertise and extensive databases, cannot devise reliable measures of corporate governance, it seems unlikely that the check-and-sum measures used by academic researchers are going have significantly better results.

The best test of MCDA effectiveness is sensitivity analysis. Which was carried out by varying the weights one at a time to measure their individual impact and the overall score robustness. A strong score on this criteria would indicate a the MCDA can perform consistently over time as new data arrives through the pipeline every year. The results from this show that changing some of the weights only cause small variations in the final Spearman's Rank correlation. The presence of small variations prove the resilience of the MCDA to modifications in individual weights, showcasing its dependability as a methodology in corporate governance research. This emphasises that the derived governance score is the result of the interactions among multiple variables, rather than being dominated by any single variable.

Overall, the MCDA method is found to be moderately effective in developing a holistic governance score that can indicate firm performance.

4.3 Research Question 3: Identify the underlying factors that significantly contribute to company performance, and analyse how companies can be classified based on their board structure traits

Factor Analysis was to uncover latent factors and reduce the high dimensional dataset contributing to company performance. Meanwhile, Cluster Analysis was used to categorise companies with similar characteristics, aiming to enhance the understanding of how governance structures influence performance within our dataset. The results of these methods have revealed interesting groups, classifiable by their distinct set of variable loadings. The findings are presented in Table 4.2.

Cluster	Factor	Name Given
A	2	Large, Equality-Focused Boards
B	1	High Ownership Boards
C	3	Traditionalist Boards
N/A	4	Small-Medium sized, Equality-Focused Boards

Table 4.2: This table represents the groups deducted as a result of the similarities found between the outcomes of Cluster and Factor Analyses.

4.3.1 Large, Equality-Focused Boards

It is apparent that companies grouped with Cluster A and Factor 2 share characteristics such as a preference for larger boards, slight preferences for dual CEOs, a higher number of independent directors, and a notable inclination towards equal voting power. This configuration suggests a governance model that values diverse perspectives and democratic decision-making processes. Larger board involvement is often associated with a broader range of expertise and viewpoints, which can enhance decision-making quality and oversight (Judge Jr and Zeithaml, 1992). The preference for equal voting power indicates a departure from hierarchical control, potentially leading to more equitable and consensus-based governing practices. This structure could be reflective of firms that prioritise corporate governance quality and stakeholder engagement, aligning with research suggesting that diverse and inclusive boards contribute positively to firm performance and risk management (Bernile et al., 2018; Perryman et al., 2016).

4.3.2 High Ownership Boards

Factor 1 and cluster B are compatible, characterised by a high positive loading for the number of directors with over 4.5% company ownership and a high level of board ownership in general. Companies in this category exhibit strong alignment between board members' interests and those of the company, as high ownership stakes incentivise directors to prioritise long-term value creation. This can reduce agency costs and cultivate a long-term goal towards growth and sustainability. However, it might also lead to potential risks associated with reduced oversight effectiveness if the board becomes too insular. The emphasis on ownership concentration is indicative of a governance model that leverages personal investment in the company to ensure dedication and align interests between shareholders and directors.

4.3.3 Traditionalist Boards

Companies falling into the Factor 3 and Cluster C grouping, exhibit traditional governance characteristics: a high percentage of male directors, high voting power, fewer ethnic minorities, and a lower percentage of independent directors. This configuration might reflect companies with more conventional governance structures, indicating a reduced emphasis on diversity and inclusion within the boardroom. High voting power and the limited presence of independent directors could suggest a more centralised control model, possibly leading to more efficient decision-making but at the risk of lower oversight quality and potential governance issues. This traditionalist approach has been critiqued for not leveraging the benefits of diversity in governance, which research shows can enhance innovation, risk management, and overall corporate performance (Dixon-Fyle et al., 2020).

4.3.4 Small-Medium sized, Equality-Focused Boards

Factor 4's defining characteristics include a high percentage of independent directors and a negative stance towards dual class voting systems, indicating companies that prioritise independent oversight and equitable shareholder representation. This structure supports a governance model emphasising the role of independent directors in providing unbiased oversight, enhancing the quality of governance, and protecting shareholder interests. The rejection of dual class voting systems aligns with a commitment to equitable treatment of shareholders, mitigating the risks associated with unequal voting power. This configuration suggests a governance philosophy that values transparency, accountability, and shareholder rights, which are key components of effective corporate governance.

4.3.5 Relationships to Tobin's Q

The subsection 3.5.2 presents the correlation between the 4 factors and Tobin's Q, aiming to shed light on the complex relationship behind the MCDA results. Factor 3 and Factor 2 are considered with respect to Tobin's Q as they express the most significant relationships out of the 4 factors.

The only positive relationship found is that of Factor 3, with a correlation of 0.112, representing the more traditional board structure. This correlation does not surpass the TOPSIS score's correlation with Tobin's Q, and consequently it is reasonable to assume that certain variables may diminish the correlation, while others may enhance it. The large loading on 'Vote Power' will benefit the correlation as it commands strong leadership, where decision making is efficient and fewer external shareholders need to be consulted. When more members have the ability to vote, innovative solutions are encouraged via encompassing a diverse range of perspectives. On the other hand, the high percentage of male directors and limited ethnic diversity are likely stunting the score, given that the regression analyses for these variables produced positive correlations. Finally, a negative factor loading for %INEDS aligns with research indicating a reduced proportion of independent directors present on the board improves performance (Bebchuk and Cohen, 2005; Muth and Donaldson, 1998; Klein et al., 2005; Shan and McIver, 2011).

Factor 2 has a strong negative correlation of -0.463 with Tobin's Q, representing the large and equal board composition. It has the most significant loading for the widely debated issue of CEO duality. This aligns with the negative weight impact given to the variable for the MCDA as well as empirical studies which find statistically negative impacts on firm performance (Duru et al., 2016; Daily and Dalton, 1994; Coles et al., 2001; Rechner and Dalton, 1991). Factor 2 also has a large factor loading on board size, with large boards being preferable, to achieve the negative correlation. This result is in line with research finding that that smaller boards are better due to productivity loss associated with large groups (Lipton and Lorsch, 1992; Jensen, 1993). Finally, Factor 2 finds that a higher percentage of independent directors, leads to a stronger negative relationship, to support the original negative MCDA "impact" that %INEDs was assigned, as well as the research of (Bebchuk and Cohen, 2005; Muth and Donaldson, 1998; Klein et al., 2005; Shan and McIver, 2011).

4.4 Link to recent literature

Academic researchers have sought to distill various governance elements into single metrics or ratings to gauge a firm's governance quality. La Porta and Lopez-de Silanes developed an index of shareholder protections, finding correlations with economic growth and market cap (1998). Gompers et al. introduced the G-score, focusing on anti-takeover measures and noting better-governed firms showed superior returns (2003), though Core et al. questioned its link to firm performance (2006). Bebchuk et al. refined this to the E-index, initially finding abnormal returns (2009), a result challenged by Johnson et al. when adjusting for industry clustering (2009), indicating mixed outcomes from governance indices research. Similarly, studies on ISS ratings and inputs offer varied findings, with some associations between governance scores and firm outcomes like stock returns and Tobin's Q, but generally lacking evidence on predicting future firm performance (Brown and Caylor, 2006; Aggarwal and Williamson, 2006; Koehn and Ueng, 2005).

Our methodology responds to the appeals to move beyond multiple regression analysis (Woodside, 2014) for corporate governance analysis. In particular, a unique approach was employed through the application of the TOPSIS method (Tzeng and Huang, 2011) to analyse an important subset of corporate governance, namely board structure, within S&P 500 companies. This research not only discovered a positive correlation between board structure and firm performance, as measured by Tobin's Q, but also validated the use of MCDA as a reliable means to generate robust scores for future evaluations through sensitivity testing.

This project also addresses the issues associated with governance metric creation transparency, providing detailed insight into the make up of a corporate governance index using the MCDA approach. This addresses the significant "confusion" surrounding the methodologies and transparency of data providers, highlighting the need for clarity in their approaches to ESG data provision (Amel-Zadeh and Serafeim, 2018).

This research aims to provide the pipeline and database for future projects on board structure to extend upon, perhaps using the suggestions within section 5.1. The Airflow pipeline integration will automate the Extraction, Transformation, and Loading (ETL) processes, and use the Directed Acyclic Graph (DAG) functionality to allow for the precise definition of tasks and their dependencies. This process ensures that data from various sources are uniformly formatted, integrated, and updated within the database. This is a vital step in preserving the database's relevancy over time.

4.5 Critical Evaluation

4.5.1 Challenges

Throughout the stages of this project, I have encountered many challenges to do with data collection, manipulation, modelling and visualisation. Some of which were anticipated during the early stages of research, and others which arose as I went along. The follwing section will highlight the main challenges faced and how they were overcome.

Data Collection & Preprocessing

Firstly, I anticipated that collecting data from multiple databases and aggregating them, often leads to fragmented and heterogeneous datasets. In particular, gaps were found in some major databases such as BoardEx's "Organisation Summary", when looking for 'Gender Ratio'. Often, where only annually updating databases were available such as Compustat's "Fundamentals Annual" database, the most recent data had not been uploaded and therefore only a fifth of 2024's data for calculating 'Board Ownership' and individual 'Blockholders' shares was available. To address this challenge, I assumed no change from the previous year and used those values to fill the missing companies' ones for the current year, allowing the analysis to produce suitable results for as large a sample as possible.

Ticker symbols were used to aggregate the variables together as this identifier was the most prevalent among the different databases. In order to get an accurate list of the current S&P500 companies, Compustat's "Unique Permanent Identifier for a Security" (Permno) number was used. This is by far the most reliable for any S&P 500 company as it never changes, being unaffected by changes in tickers, CUSIPs (Committee on Uniform Security Identification Procedures), name alterations, and other events. Consequently, the initial list of companies was compiled from two CRSP databases: one featuring the Permnos for S&P500 companies $CRSPIndexes, dailyS\&P500table$, including join and exit dates and another containing both Permnos and company tickers $CompustatCRSPMerged(CCM), CCMLookup$ using a single SQL query to join these datasets based on the Permnos.

MCDA Weighting

One of the larger challenges of this project was finding a suitable MCDA weighting method. This varies depending on the type of data present and it almost always requires some sort of user preference to be specified and therefore is subject to bias. I considered using entropy weighting, analytical hierarchy process weighting and the 'CRITIC' method, amongst others.

Entropy weighting was the only method to not involve specifying preferences, which works by assigning the weights based of the "entropy" or variability of each parameter. The issue stems from the dataset's mix of binary and continuous variables, which could heavily skew the entropy weighting method, rendering it unsuitable.

Analytical hierarchy process or AHP weighting, which is often used in conjunction with 'PROMETHEE' methods, as demonstrated by (Guney et al., 2020), was not chosen for analysis. This approach requires users to rank variables relative to one another, which was a requirement deemed unsuitable for our context. Our variables do not lend themselves to direct comparison, instead, their relevance was determined individually, based on prior research unique to each variable.

Consequently, the final weighting method involved a combination of prior research and the observable correlation from individual regression analyses performed to make the final weights, this ensured weights corresponding to the dataset's characteristics were used, whilst they were still in line with the current research. Information on the individual weights reasoning is contained in subsection 3.3.3.

Airflow Pipeline Integration

I paired with another student to get our data collection analysis python scripts integrated with the Airflow pipeline provided by Yong Chen. However, this proved more difficult due to the lack of instruction available on setting up the pipeline. Unfortunately, Yong was no longer studying at Edinburgh and we could not make contact after initial communication. However, the setup challenges were resolved later on with the assistance of more experienced colleagues.

4.5.2 Limitations

Noise & Endogeneity

In corporate finance research, experts can often overlook sources of endogeneity. Notably, how a company's current management practices might be shaped by its past performance. Ignoring this link can skew research findings, especially since real-world examples or clear-cut evidence is hard to come by, forcing researchers to rely on historical data analysis. To overcome endogeneity, where possible, the research has included the analysis of time-series data from 2007, which was the earliest available date. To mitigate the challenge of noisy data, the research has implemented dimensionality reduction techniques such as PCA before the Cluster Analysis.

One Size Fits-All Approaches

Within the field of corporate governance research and the broader finance sector, nearly all casual relationships are very complex, with many non-linear correlations present. Performance is influenced by a host of different variables, including basic economic principles like supply and demand, political situations, rates of innovation and more. The overwhelming conclusion from the complexity of results produced is that one-size-fits all approaches will end up skipping a lot of the governance detail specific to each companies situation and thus forming a score based off partial information.

Given the varied outcomes in prior research concerning most of the variables considered, it's expected that their aggregation will compound the complexity of correlating them to performance. Therefore, even a small correlation of 0.145 gains significance in fulfilling the research objectives and bolstering the credibility of the MCDA approach.

Decreasing dataset over time

In order to perform the MCDA, Cluster Analysis and Factor Analysis effectively, it is essential that the dataset is free from missing values. Consequently, during preprocessing, the variables were merged together on the intersection of tickers across both dataframes to create the dataset. This approach meant that, as the availability of specific variable data from earlier years decreased, the size of the final table was correspondingly diminished. Figure 4.1 illustrates the volume of data accessible for previous years.

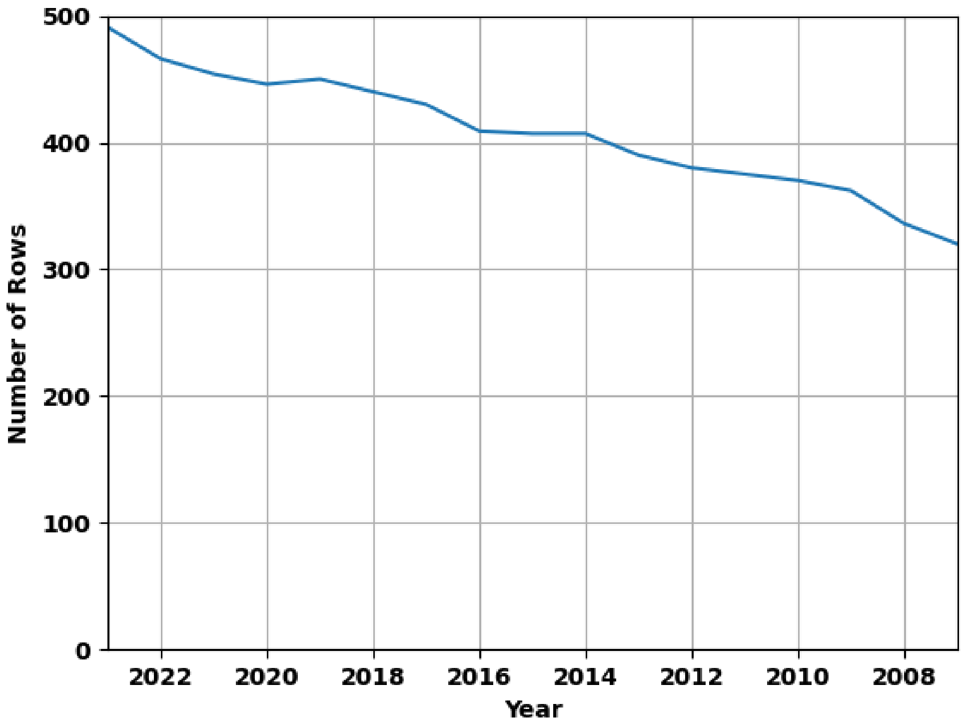

Figure 4.1: Line graph representing the number of rows in the datasets created, which were available from previous years

Tobin's Q as a performance metric

Whilst being a widely accepted measure of performance, there has been recent debate in the literature about its efficacy (Bendle and Butt, 2018; Edeling and Fischer, 2016).The debate arises from the argument that Tobin's Q can be exhibit short-term volatility, being influenced by market perceptions, investor sentiment, and external economic factors, rather than just the intrinsic value or effectiveness of the company's initiatives. Furthermore, a Tobin's Q value may lag behind actual performance improvements, as market perceptions often take time to adjust to changes.

Tobin's Q was chosen as it offers a well rounded perspective by comparing the market value of a firm's equity and debt to the replacement cost of its assets (Tobin, 1969; Lindenberg and Ross, 1981). Research has demonstrated that Tobin's Q is a significant predictor of future investment opportunities and firm performance (Chung and Pruitt, 1994; Perfect and Wiles, 1994).

Chapter 5

Conclusion

This project links into recent literature on corporate governance by addressing the increasingly recognised importance of environmental, social, and corporate governance factors in investment decision-making and corporate performance assessment. Previous research has often focused on individual aspects of board structure, such as board diversity or CEO duality, and presented mixed findings on their impact on firm performance. This dissertation attempts to bridge these disparate strands by considering a wide range of board structure characteristics in its analysis, thereby providing a more holistic view of corporate governance quality. In doing so, it addresses a critical research gap: the lack of a comprehensive, empirically tested model that can analyse company performance based on a wide array of governance indicators.

The MCDA not only adds depth to the academic discussion on corporate governance but also provides practical insights for investors, policymakers, and companies. The research is valuable in that it synthesises multiple dimensions of board structure into a single, comprehensive governance score, allowing for a direct comparison between companies based on the strength of their board structures. The findings suggest that the governance score, developed through MCDA, shows a mild positive correlation with Tobin's Q. This indicates a degree of success in capturing the performance implications of board structure. Additionally, the relationship is complex and influenced by underlying factors which are only attainable by incorporating factor and Cluster Analysis to aid our understanding of governance structures. In doing so, we can identify distinct profiles of companies based on their governance traits and how these profiles relate to performance.

This study faced several limitations and challenges, primarily related to data collection, availability, and the inherent complexities of adopting holistic approaches to governance analysis. These issues, largely beyond the control of this research are deeply rooted within the field of governance studies. Despite these hurdles, the establishment of a data pipeline will ensure that this research will continue to provide insights for corporate governance studies, assisting future research as new data and patterns emerge.

5.1 Future Work

MCDA has demonstrated its potential as a valuable instrument for advancing research in corporate governance analysis. Consequently, I advocate for the extended application of this technique within further research.

This study focused on board structure as a key aspect of corporate governance, laying the groundwork for future research to explore a broader range of governance variables. While this expansion may add complexity, employing factor and Cluster Analysis could enable the discovery of causal relationships and latent variables, enriching our understanding of corporate governance dynamics. Similarly, future work should expand the dataset to companies outside of the S&P500, in particular assessing the governance characteristics associated with privately owned companies, smaller enterprises, or firms in different markets. While this would introduce some challenges due to limited data availability, especially for private firms, it would still provide useful insight and comparable results.

This research could be further refined by concentrating on the causal relationship between governance and performance metrics, such as long-term company performance. This involves training the models on historical data, and analysing recent changes with respect to those variables. Specifically, this method could be employed to examine the effects of specific financial events over a designated period. For example, the repercussions of financial crises, global pandemics, or market anomalies such as the dot-com, cryptocurrency or AI bubbles.

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Appendix A

List of Abbreviations

- *ESG* – Environmental, Social and Corporate Governance
- *S&P500* – Standard and Poor's 500: a stock market index tracking the stock performance of 500 of the largest companies listed on stock exchanges in the United States.
- *MCDA* – Multi-Criteria Decision Analysis
- *Tobin's Q* – Measure of performance in this research
- *WRDS* – Wharton Research Data Services
- *API* – Application Programming Interface
- *CEO* – Chief Executive Officer
- *ROA* – Return on Assets
- *ROE* – Return on Equity
- *IPO* – Initial Public Offering
- *BoardEx* – Data company
- *Compustat* – A database, owned by a division of Standard and Poor's Global.
- *ISS* – Institutional Shareholder Services: Data provider
- *SQL* – Structured Query Language: Syntax used for pulling variables from databases.
- *PROMETHEE* – Preference ranking organisation method for enrichment evaluation: Type of MCDA method
- *AHP* – Analytical Hierachy Process: A MCDA weighting method.
- *TOPSIS* – Technique for Order of Preference by Similarity to Ideal Solution: MCDA method used in this research.
- *SSE* – Sum of Squared Errors

- *PCA* – Principal Component Analysis: Dimensionality reduction technique used in this research.
- *DTW* – Dynamic Time Warping:
- *KMO* – Kaiser-Meyer-Olkin
- *CSV* – Comma Delimited Version
- *GMI* – Governance Metrics International
- *TCL* – (a rating produced by The Corporate Library).
- *CSRHub* – Corporate Social Responsibility Hub
- *ETL* – extration, transformation and loading processes involved in an Airflow pipeline
- *DAG* – directed acyclic graph. Part of the Airflow set up.
- *Permno* – Compustat's "Unique Permanent Identifier for a Security" number.
- *CUSIP* – Committee on Uniform Security Identification Procedures,
- *CRSP* – Center for Research in Security Prices
- *CRITIC* – Criteria Importance Through Inter-criteria Correlation: MCDA weighting method
- *COVID-19* – Global Corona Virus Pandemic
- *AI* – Artificial Intelligence

Variables:

- *Board Size* – The number of directors present on the board.
- *%INEDS* – The percentage of Independent Non-Executive Directors present on the board.
- *Board Ownership* – The total proportion of ownership held by the directors on the board.
- *Blockholders* – The number of individual directors who own over 4.5% of the company stock.
- *CEO Dual* – The presence of a dual CEO, 1 if present and 0 otherwise.
- *Gender Ratio* – The proportion of male directors present on the board.
- *Ethnic Ratio* – The proportion of ethnic minorities present on the board.
- *Dual Class* – The presence of Dual class voting, 1 for present and 0 otherwise.
- *Vote Power* – The proportion of board members with the right to vote.
- *Tobin's Q* – The calculated Tobin's Q value for this company.

Appendix B

Github Repository

This project's the github repository's project's URL is:

`https://github.com/TobyWhittome/BoardDiversity_WRDS`

The repository contains a README.md file containing all the set up instructions and required dependencies to run the python scripts.