Faculty of Business and Law

MSc. Financial Technology

Inventor CEOs and Firm Value in the U.S Stock Market: Evidence from Machine Learning Regressions

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Innovation is the specific instrument of entrepreneurship; The act endows resources with a new capacity to create wealth- Peter .F. Drucker- 2000

CHAPTER 1: INTRODUCTION

1.1 Research Background

In the evolving world of business today the position of Chief Executive Officer (CEO) has undergone changes. CEOs now have a scope of responsibilities beyond the day, to day management tasks as they also contribute significantly to fostering innovation and moulding the culture within organizations. Within this group of CEOs Inventor CEOs are often recognized for their technological innovation background, ownership of patents or establishment of tech startups. They stand out for their combination of leadership skills and technical know how (Bostan & Mian 2019).

Research on corporate leadership has primarily focused on attributes such as educational background, risk-taking behaviour, leadership style, and investment knowledge, and their effects on firm performance. For instance, (Custódio et al., 2019) found that general managerial skills spur innovation, which positively influences firm performance. Similarly, (Suherman et al., 2023) highlighted that CEO characteristics like age and duality positively influence the performance of Vietnamese banks. Despite these findings there is still a gap, in the research regarding how inventor CEOs influence a company's value. While some studies indicate that inventor CEOs boost company performance by promoting innovation and strategic planning (Seru, 2014) others point out downsides like overconfidence and excessive risk taking (as discussed by Hirshleiferm et al., 2012). Conventional statistical models may not fully capture the connections, between CEO traits and company success (see Graham et al., 2013).

With access, to patent information this research examines the number of patents owned by CEOs as a measure to identify Inventor CEOs. Patents serve as an indication of a CEOs endeavours and their direct impact on fostering innovation within the company offering a more precise and objective assessment compared to indicators such as technical education and R&D investments, which also provide valuable insights. Furthermore, the practical importance of this study is emphasized by recent advancements from companies and the value it has added to them. For instance, the innovative leadership of CEOs at technology giants like Tesla and Nvidia has not only propelled these companies to market dominance but also influenced broader industry trends. These instances underscore the role of Inventor CEOs, in shaping landscapes and driving significant value generation.

1.2 Aims and Questions

This study seeks to explore the intricate dynamics between CEO innovation attributes and firm performance, specifically focusing on CEOs within S&P500 companies. The research is guided by the one key question:

- ***Do inventor CEOs positively impact firm value?***

1.3 Study Significance

The importance of this study lies in its potential to bridge a critical gap in the current literature and its practical implications for corporate governance and strategy. As the global environment becomes increasingly competitive and innovation-driven, understanding the characteristics that contribute to effective leadership is paramount. This research offers several key contributions.

Firstly, by focusing on inventor CEOs, this study emphasizes the importance of technical expertise and innovative capabilities in executive leadership. Unlike traditional CEOs, Inventor CEOs bring a unique perspective to the corporate world, one that blends deep technical knowledge with strategic vision. This duality is particularly relevant in high-tech industries where rapid innovation is crucial for maintaining competitive advantage. For example, (Bostan & Mian, 2019) have shown that firms led by inventor CEOs often experience enhanced innovation outcomes, suggesting that such leaders are more adept at fostering an environment conducive to technological advancements.

Furthermore, this study employs advanced machine learning techniques to analyse the direct impact of inventor CEOs on firm value. Traditional econometric models of ten fall short in capturing the complex, non-linear relationships inherent in leadership and firm performance. By leveraging machine learning, this research not only provides more accurate and nuanced insights but also sets a precedent for future studies in corporate finance and management to adopt a similar methodology (Brynjolfsson & McElheran, 2016). This methodological innovation is critical as it opens new avenues for analysing large datasets and uncovering patterns that were previously obscured (Mullainathan & Spiess, 2017; Varian, 2014).

Thirdly, the practical implications of this study are profound. For firms and boards considering the appointment of new CEOs, understanding the potential benefits and risks associated with inventor CEOs is invaluable. Companies in innovation-intensive industries can particularly benefit from such insights, allowing them to make more informed decisions that align with their strategic objectives (Henderson & Cockburn, 1994). The findings could lead to a reassessment of how leadership qualities are evaluated and prioritized in the selection process, potentially shifting the focus towards technical and innovative prowess.

Moreover, this study contributes to the broader discourse on the role of leadership in driving firm performance. As firms navigate the complexities of globalization, technological disruption, and market volatility, the ability to innovate becomes a key differentiator. Inventor CEOs, with their unique blend of skills, are ideally positioned to steer companies through such challenges. This research underscored the importance of aligning leadership selection with the firm's innovation goals, thereby enhancing its long-term value-creation potential (see Galasso & Simcoe, 2011; Hirshleifer et al., 2012).

Finally, from an academic standpoint, this dissertation enriches the existing body of knowledge by integrating insights from finance, management, and technology. The interdisciplinary nature of this research also encourages future studies to explore these tools, thereby advancing the methodological rigour in the field (Custodio et al., 2019). By incorporating perspectives from various disciplines, the study provides a holistic view of the impact of inventor CEOs, fostering a deeper understanding of how leadership influences innovation and firm performance.

In conclusion, this study is not merely an academic exercise but a crucial investigation into how leadership, particularly that of inventor CEOs, impacts firm value. Its findings are expected to have significant implications for both theory and practice, paving the way for more innovative and strategically aligned leadership in the corporate world.

1.4 Methodological Overview

This study aims to analyse the impact of CEOs who possess inventing abilities on the overall value of companies featured in the S&P 500 index. The study will focus on the period from 2019 to 2023. The financial facts, including the company's worth and total assets, are obtained from Bloomberg. The patent data utilised for identifying Inventor CEOs is acquired from USPTO and PATENTSCOPE. The sample consists of 31 firms from several industry areas, with the exception of utilities and banking.

Tobin's Q is used as a metric to assess the worth of a firm and is considered the variable that is influenced by other factors. The primary independent variables consist of Inventor_CEO, a binary variable that indicates if the CEO is an inventor, The control variables used in this study are capital R&D expenditure to asset (RDAST), expenditure to assets ratio (CAPXAST), book-to-market ratio (BM), return on assets (ROA), and industry growth rate.

The study initially use the Ordinary Least Squares (OLS) regression technique to establish a fundamental comprehension of the connections between the variables. Furthermore, sophisticated machine learning approaches, such as Gaussian Process Regression and Ensemble Learning, are utilised to capture intricate, non-linear relationships that may not be sufficiently handled by conventional regression techniques. The implementation of these models is conducted using MATLAB, which provides advanced analytical capabilities and dependable validation techniques. The objective of this multifaceted method is to offer a thorough examination of the influence of Inventor CEOs on the value of a company.

1.5 Research Structure

This dissertation is divided into five chapters to comprehensively explore the impact of inventor CEOs on firm value. This chapter provides a general background, aim and objectives, significance, and methodological overview, setting a solid foundation for the entire study. The second chapter critically examines existing literature, comprising published work and the development of research hypotheses. This chapter particularly will dive into the methodology, explaining the data collection methods and outlining the subsequent analysis techniques. This chapter is the bedrock for the orderly examination of the research questions. Chapter four is dedicated to the interpretation of results, findings, and hypotheses, highlighting the relationships discovered. Chapter five concludes the research work, drawing conclusions and addressing limitations while providing commentary on future research.

CHAPTER 2: LITERATURE REVIEW

This literature review critically examines the existing research on the impact of inventor CEOs on firm value, with a particular focus on leveraging advanced machine learning techniques. The chapter synthesizes findings from top academic journals to provide a comprehensive background, identify gaps in the current literature, and establish a theoretical framework for the present study.

2.1 CEO Characteristics and Firm Performance

The relationship between CEO characteristics and firm performance has been a significant focus in corporate finance and management literature. Among these characteristics, is the role of inventor CEOs. Existing literature underscored the importance of CEOs' managerial skills and educational background. In influencing firm performance. (Custódio et al., 2013) provide empirical evidence that CEOs with robust managerial skills significantly contribute to firm innovation and performance. These skills encompass strategic vision, operational efficiency, and the ability to navigate complex corporate environments. (Bertrand & Schoar, 2003) further emphasize the significant influence of educational background, noting that CEOs with technical and business education backgrounds often exhibit superior strategic foresight and decision-making capabilities.

Inventor CEOs, characterized by their technical expertise and innovative mindset, bring a unique dimension to corporate leadership. (Bostan & Mian, 2019) highlight that firms led by inventor CEOs typically exhibit enhanced innovation outcomes. These CEOs leverage their deep technical knowledge to foster a culture of continuous innovation, aligning corporate strategy with technological advancements. Lin et al. (2023) corroborates this view, demonstrating that inventor CEOs are instrumental in driving R&D initiatives and translating technological innovations into marketable products.

2.2 Innovation and Firm Value

Innovation is a critical driver of firm value, with R&D expenditure serving as a key indicator of a firm’s commitment to innovation. The role of innovation in enhancing firm performance. Is well-documented in literature.

(Hall et al., 2000) provide robust evidence that evidence that higher R&D spending is positively correlated with improved market valuation and profitability. This relationship underscores the importance of sustained investment in R&D for fostering long-term competitive advantage. Firms that consistently invest in R&D are better positioned to develop new products, improve processes, and maintain a competitive edge in the market.

The Resource-Based View (RBV) and Dynamic Capabilities Framework offer valuable theoretical perspectives on the link between innovation and firm value. (Barney, 1991) posits that firms with unique, valuable, and imitable resources, such as proprietary technologies and innovative capabilities, can achieve sustained competitive advantage.

2.3 Machine Learning in Financial Analysis

The application of machine learning in financial analysis has revolutionized the field, offering new ways to predict firm performance and analyse complex financial data. Machine learning techniques, including regression models, classification algorithms, and neural networks, have demonstrated superior capabilities in processing large datasets and identifying complex, non-linear relationships.

(Brynjolfsson & McElheran, 2016) argue that machine learning surpasses traditional econometric models in providing more accurate and clear insights.

In financial research, machine learning has been employed in various applications, such as predicting stock prices, assessing credit risk, and analysing financial sentiment. Its effectiveness has been highlighted in the field of fintech lending as it demonstrated superior predictive accuracy and the ability to handle vast amounts of data compared to traditional methods (see Jagtiani and Lemieux, 2019). This study employs similar techniques to analyse the impact of inventor CEO on firm value.

2.4 Hypothesis Development

Based on the extensive review of the literature, a primary hypothesis is formulated for this study to empirically test the relationship between inventor CEOs and firm value using advanced machine learning techniques.

Hypothesis (H1)

$$\boldsymbol{TOBIN_i = \alpha + \beta_0 INVENTOR\_CEO + \beta_1 CTRLS + \varepsilon}$$

The rationale behind this hypothesis is grounded in the evidence that inventor CEOs, due to their technical expertise and innovative mindset, can significantly enhance a firm's innovation outcomes. This, in turn leads to increased firm value as measured by metrics such as Tobin's Q. Studies have provided empirical support for this hypothesis (see Bostan & Mian 2019, and Lin et al., 2023) demonstrating that firms led by inventor CEOs exhibit superior innovation performance and market valuation.

CHAPTER 3:

3.0 METHODOLGY

This chapter is a comprehensive explanation of the specific research methods that will be used to examine the influence of inventor CEOs on the value of companies included in the S&P 500. The goal of this study is to provide extensive insights into the relationship between CEO characteristics and company success. To achieve this, the research will employ both conventional econometric instruments and innovative machine-learning methodologies. A comprehensive analysis will be conducted within the study's timeframe, spanning from 2019 to 2023. The research benefits from the inclusion of extensive datasets from Bloomberg, USPTO, WRDS, and PATENTSCOPE, which are renowned for their reliable and comprehensive financial, executive and patent data. These datasets form the foundation of the study, enabling a robust investigation into the impact of the study, enabling a robust investigation into the impact of inventor CEOs on firm value.

3.1 Data Sources

The data for this study are sourced from Bloomberg, USPTO, and PATENTSCOPE, guaranteeing a comprehensive and reliable dataset for analysis. Bloomberg offers precise financial data essential for comprehending company performance indicators such as Tobin's Q, total assets, book-to-market ratios, and return on equity. This source is renowned for its precision and comprehensive scope, rendering it appropriate for scholarly investigation in the fields of finance and corporate governance (Fama & French, 1992). The USPTO and PATENTSCOPE databases are utilised to discover inventor CEOs by analysing patent data. These databases include comprehensive information about submitted and granted patents, including the names of inventors, assignees, and pertinent dates. These databases provide accurate and unbiased measurement of a CEO's innovative capability (Griliches, 1990). By integrating data from various trustworthy sources, one can gain significant insights about the convergence of leadership, innovation, and company performance.

3.2 Data Sample and Characteristics

The sample consists of 31 firms from the S&P 500. The selection of these companies was determined by the availability of comprehensive data on financial metrics and CEO qualities covering the period from 2019 to 2024. The choice of this time frame was intended to portray a current investigation and to mirror recent modifications. The selection criteria ensure that the sample is representative, allowing for a thorough examination of the research topics.

All organisations included in the sample were required to have consistent data on both the qualities of the CEO and the financials of the company. (Brown & Petersen, 2009) and (Hall & Lerner, 2010) exemplify research demonstrating the significant impact of innovation on certain businesses. The emphasis on industries that heavily rely on technology aligns with the findings of these studies. This approach guarantees a thorough examination of how inventor CEOs impact the value of a corporation in different industry settings. The sample encompasses companies from several industries, excluding the finance and utilities sectors. There are various peculiarities that have to do with the banking sector and its approach to risk and innovation make this area a poor candidate for this type of study (Adams & Mehran, 2012). For utility companies, the decision to avoid them was grounded in the fact that these industries are overregulated, and innovations that can be implemented there are limited by the scope of their activities (Joskow, 2008).

3.3 Classifying CEO

The classification of Inventor CEOs entails the identification of CEOs who possess patents, which suggests a tangible contribution to innovation. This classification is predicated on patent data obtained from the United States Patent and Trademark Office (USPTO) and PATENTSCOPE databases, which offer comprehensive and dependable information regarding patents issued to individuals. Inventor CEOs are CEOs who have at least one registered patent.

This classification method adheres to the established practices in the literature, which regard patent holdings as a direct indicator of an individual's technical expertise and inventive capability (Griffith et al., 2004) Inventor CEOs are distinguished from their non-inventor counterparts by the tangible evidence of their contributions to technological advancements that patents provide.

The primary criterion for classifying Inventor CEOs is patent data, which provides numerous benefits. This measure of innovation is both objective and quantifiable, which is consistent with prior research that underscores the significance of patents in capturing the inventive activities of both individuals and organisations (Trajtenberg, 1990). In addition, this method circumvents the constraints of employing proxies such as technical education or R&D expenditure, which, while they suggest a focus on innovation, do not directly quantify an individual's inventive output.

Proxies, including technical education and R&D expenditure, are valuable indicators of a CEO's potential to drive innovation; however, they lack the specificity and directness of patent data. Technical education is essential for the comprehension and management of technological initiatives, as it is indicative of a CEO's formal training and knowledge base (Murphy & Zábojník, 2004). Similarly, R&D expenditure is frequently influenced by the CEO's strategic vision and priorities and serves to emphasise a company's dedication to innovation (Hall & Lerner, 2010). However, patent holdings establish a distinct and direct connection that neither of these proxies can replicate.

Additionally, the incorporation of patent data into the analysis enables a more sophisticated comprehension of the influence of Inventor CEOs on firm performance.. This study endeavours to offer a more precise and comprehensive evaluation of the impact of these distinctive leaders on corporate success by distinguishing CEOs based on their actual contributions to innovation. This classification method guarantees that the analysis is concentrated on CEOs who have demonstrated a significant contribution to technological advancements, thereby offering a more profound understanding of the correlation between CEO characteristics and firm value.

3.4 RESEARCH DESIGN

3.5 MODEL SPECIFICATION

This study utilises an economic model to analyse the impact of Inventor CEOs on firm value, as quantified by Tobin's Q. The model integrates crucial independent variables and control variables to offer a thorough examination of the elements that influence the success of an organisation.

The dependent variable we are focussing on in our model is Tobin's Q, which is a well-established metric used to evaluate the worth of a company. It is produced by dividing the market value of a company by the replacement cost of its assets. Tobin's Q is a comprehensive measure that represents corporate performance by considering both the market's perception and the intrinsic value of the firm's assets (Hall et al., 2000).

To evaluate the influence of CEOs who are also inventors on the value of a company, the model incorporates a binary independent variable called Inventor CEO (INV_CEO). This variable determines whether a CEO is classed as an inventor, depending on patents owned by the CEOs. Furthermore, the variable of R&D Intensity (RD_AST) is incorporated as a continuous measure, which indicates the firm's dedication to innovation using its investment in research and development (Brown & Petersen, 2009; Hall & Lerner, 2010).

3.6 Control variables

The impact of Inventor CEOs on firm value is systematically evaluated by incorporating a carefully selected set of control variables, each of which has been selected for its established relevance in the literature on corporate innovation and performance. The firm's dedication to innovation is reflected in the R&D intensity (RDAST), which is calculated as the ratio of R&D expenditure to total assets. This control is essential because firms with a higher R&D intensity frequently generate more innovation outputs, which can increase market valuation (Brown & Petersen, 2009). We guarantee that the impact of Inventor CEOs on firm value is not muddled by variations in innovation investments by controlling for R&D intensity. Consequently, we isolate the specific contribution of CEO-driven innovation.

Another critical control variable is capital expenditure intensity (CAPXAST), which is defined as the ratio of capital expenditures to total assets. This metric differentiates between organisations that prioritise intangible assets, such as intellectual property, and those that concentrate on physical asset investments. The incorporation of CAPXAST enables us to account for the influence of physical investments on firm performance, thereby ensuring that the observed effects are not solely the result of varying investment strategies (Hall & Lerner, 2010). In addition, the book-to-market ratio (BM) is incorporated to represent market perceptions of a company's valuation in relation to its book value. Investor sentiment and firm value are frequently influenced by higher BM ratios, which frequently indicate undervaluation and potential for growth (Fama & French, 1992). By controlling for BM, biases that may arise from market undervaluation or growth expectations are mitigated, which could otherwise confuse the relationship between Inventor CEOs and firm value.

Furthermore, operational efficiency is captured through the inclusion of return on assets (ROA), a profitability ratio that quantifies the effectiveness of a company's asset utilisation in generating earnings. (Graham et al., 2013) have observed that firms with a higher return on assets (ROA) exhibit superior performance, which is directly correlated with a higher firm value. By incorporating ROA, we account for operational efficiency fluctuations that could otherwise distort the influence of Inventor CEOs. Finally, the industry growth rate is regulated to account for the macroeconomic and sector-specific trends that affect the performance of the firm. (Adams & Mehran, 2012) suggest that firms in industries that are swiftly expanding may experience higher market valuations as a result of favourable industry conditions rather than firm-specific factors. This comprehensive set of constraints guarantees that our analysis isolates the distinctive contributions of Inventor CEOs to firm value, thereby enabling a nuanced and robust comprehension of their impact in the face of a variety of confounding factors.

$$\boldsymbol{TOBIN_i = \alpha + \beta_0 INVENTOR\_CEO + \beta_1 CTRLS + \varepsilon}$$

3.7 Machine Learning Regressions

This study utilises a variety of sophisticated machine learning algorithms in addition to the conventional linear regression model to improve the accuracy and robustness of our analysis. Among these algorithms are Neural Networks, Support Vector Regression (SVR), and Random Forest Regression, each of which was chosen for its distinctive capabilities in managing intricate, non-linear relationships within extensive datasets (Brynjolfsson & McElheran, 2016).

(Breiman, 2001) has found that Random Forest Regression is particularly beneficial for capturing interactions between variables and providing insights into variable importance. (Drucker et al., 1996) have employed SVR due to its capacity to effectively manage the non-linear boundaries within the data and its efficacy in high-dimensional spaces. Neural Networks provide a sophisticated method for modelling the intricate dynamics between CEO characteristics and firm value due to their ability to uncover profound, complex patterns (Heaton et al., 2017).

We employ cross-validation techniques to guarantee the reliability of our models, which prevent overfitting and validate the predictive power of the model. The primary metrics for assessing the efficacy of a model are R-squared (R^2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). RMSE offers a quadratic scoring formula that penalises larger errors more severely, whereas MAE provides a straightforward measure of the average magnitude of prediction errors. R-squared is a metric that quantifies the model's explanatory power by indicating the proportion of variance in the dependent variable that is predictable from the independent variables (Friedman, Hastie, & Tibshirani, 2001).

As assessed by Tobin's Q, we propose that the presence of an inventor CEO will have a beneficial impact on the value of the firm. The positive impact of Inventor CEOs on firm value is anticipated to be amplified by higher R&D investments, as the level of R&D expenditure moderates this relationship. The objective of this study is to contribute to the broader literature on corporate leadership and innovation by offering more precise and nuanced insights into the role of Inventor CEOs in enhancing firm value through the use of advanced machine-learning techniques.

In the current competitive and innovation-driven market, this model specification establishes the groundwork for a thorough examination of how Inventor CEOs, who are distinguished by their technical proficiency and innovative leadership, can enhance the performance of their organisations. This study endeavours to address the lacuna in the existing literature and provide practical implications for strategic decision-making and corporate governance by employing rigorous econometric and machine-learning methodologies.

3.8 Summary Statistics

Table 1 reports the description of variables used in this study. The summary statistics include the sample size (N), mean, minimum (Min), maximum values (Max), and standard deviation (Std. Dev.). The variables include firm value (FirmValue), research and development intensity (RDAST), capital expenditure intensity (CAPXAST), book-to-market ratio (BM), return on assets (ROA), and industry growth rate (Industry_Growth_Rate). The sample covers firm-year observations from 2019 to 2023. All variables are defined in Appendix A.

Variable	Obs	Mean	Std. dev.	Min	Max
ID	155	16	8.973265	1	31
Year	155	2021	1.418798	2019	2023
TOBINS_Q	155	1.575838	0.507916	0.718864	2.948866
INV_CEO	155	0.322581	0.468979	0	1
RDAST	155	0.077147	0.060085	0	0.312258
CAPXAST	155	0.031036	0.028485	0.003787	0.156764
BM	155	0.176654	0.180152	-0.14957	0.941718
ROA	155	0.094273	0.123465	-0.30515	0.762488
Industry_G~e	150	0.007509	0.030439	-0.07234	0.194362

Table 1 presents a summary of the main factors examined in this study, emphasising notable differences and distinctive features within the sample from 2019 to 2023. The Tobin's Q ratio (TOBINS_Q) has an average value of 1.575838 and a measure of dispersion of 0.507916, with values ranging from 0.718864 to 2.948866. This suggests that there are significant differences in the market values of enterprises compared to the costs of replacing their assets, indicating varying levels of efficiency in strategic asset management.

The proportion of CEOs who are inventors (INV_CEO), representing 32.26% of the sample, has a standard deviation of 0.468979 due to its binary characteristic. This statement highlights the unique position of Inventor CEOs and suggests that there may be variations in their impact on the operation of the company. RDAST, which measures the intensity of research and development, has a mean of 0.0771468 and a standard deviation of 0.0600848. CAPXAST, which measures the intensity of capital expenditure, has a mean of 0.031036 and a standard deviation of 0.0284845. The heterogeneity in degrees of commitment to innovation and physical investments highlights the need of recognising the strategic diversity among organisations.

In addition, the book-to-market ratio (BM) and return on assets (ROA) provide insights into the financial well-being and operational effectiveness of the firms, with average values of 0.1766542 and 0.0942733, respectively. The considerable variation in BM (-0.149574 to 0.9417182) and ROA (-0.305153 to 0.762488) values indicates substantial disparities in market valuations and profitability. The industry growth rate (Industry_G~e) exhibits significant variation, with an average of 0.0075088 and a standard deviation of 0.0304391. This indicates the presence of varied external factors that influence business performance. The figures collectively provide a detailed overview of the many characteristics and strategic decisions of firms, which are crucial for analysing the distinct contributions of Inventor CEOs to the value and innovation of the company.

3.9 Summary Statistics by CEO type

Table 2 presents the summary statistics for firms led by Inventor CEOs compared to those led by non-Inventor CEOs. The table includes key financial and operational metrics such as Tobin's Q, R&D intensity (R&D/AST), capital expenditure intensity (CAPX/AST), book-to-market ratio (BM), return on assets (ROA), and industry growth rate.

		mean	std	min	max
Inventor CEOs	**TOBINS_Q**	1.763448285	0.56749338	0.83382175	2.948866008
	INV_CEO	1	0	1	1
	R&D /AST	0.077898819	0.06348368	0	0.312257538
	CAPX/AST	0.037714037	0.031431801	0.007530801	0.156763942
	BM	0.185388031	0.17036238	0.020960295	0.612136362
	ROA	0.1306183	0.163803525	-0.289461	0.762488
	Industry_Growth_Rate	0.0103385	0.03819692	-0.072340844	0.194361731
Non-Inventor CEOs	**TOBINS_Q**	1.486500175	0.45309271	0.718863659	2.747245273
	INV_CEO	0	0	0	0
	R&D /AST	0.076788629	0.058707906	0	0.2566357
	CAPX/AST	0.027856033	0.026539026	0.003786707	0.145174522
	BM	0.172495225	0.18528142	-0.149573963	0.941718183
	ROA	0.076966095	0.094831283	-0.305153	0.332221
	Industry_Growth_Rate	0.006177159	0.026121539	-0.047396803	0.050414619

The summarised statistics for firms led by Inventor CEOs and non-Inventor CEOs are presented in Table 2, which demonstrates significant differences in key financial and operational metrics. In comparison to non-Inventor CEO firms (mean 1.486500), firms with Inventor CEOs demonstrate a higher Tobin's Q (mean 1.763448), which suggests that their market valuations are higher in relation to its asset replacement costs. The standard deviation of 0.567493 indicates that the Tobin's Q of Inventor CEO firms is more variable, which suggests that there are higher perceived innovation potential and diverse market expectations.

The mean R&D intensity (RDAST) of inventor CEO firms is marginally higher than that of non-Inventor CEO firms (mean 0.076789), with a larger standard deviation (0.063484 vs. 0.058708). This suggests that Inventor CEOs are more likely to lead a diverse range of R&D investments, including radical innovations and incremental advancements. Furthermore, the capital expenditure intensity (CAPXAST) of Inventor CEO firms is significantly higher (mean 0.037714) than that of their counterparts (mean 0.027856), which indicates a strategic emphasis on tangible asset investments to facilitate innovative activities. A diverse array of investment strategies aimed at enhancing firm capabilities is indicated by the broader range and higher variability in CAPX/AST for Inventor CEO firms.

Additionally, inventor CEO firms exhibit superior operational efficiency, as evidenced by a higher return on assets (ROA) mean of 0.130618 compared to 0.076966 for non-Inventor CEO firms. This underscores the improved profitability and asset utilisation of inventor CEO firms. Inventor CEO firms are situated in more dynamic industries, as evidenced by a higher mean industry growth rate (0.010339 vs. 0.006177), despite the higher variability in ROA, which suggests the high-risk nature of their innovation initiatives. This position is expected to generate additional development opportunities and emphasise the strategic advantage of having Inventor CEOs who can effectively navigate and capitalise on the rapidly changing industry landscapes.

CHAPTER 4

4.0 Result and Analysis

Table 3 provides a comprehensive view of the relationships between key variables in the study. Each cell in the matrix represents the correlation coefficient between two variables, with asterisks indicating the significance levels: $p < 0.10$ (), $p < 0.05$ (), and $p < 0.01$ (). This analysis is further supported by the Variance Inflation Factor (VIF) values, which confirm the absence of multicollinearity concerns.

	ID	**Year**	**TOBINS_Q**	**INV_CEO**	**RDAST**	**CAPXAST**	**BM**	**ROA**	**Indust~e**
ID	1								
Year	0.0056	1							
TOBINS_Q	0.0389	-0.0872	1						
INV_CEO	0.1458*	0.0082	0.2526***	1					
RDAST	-0.1878	-0.1052	0.3697***	0.0263***	1				
CAPXAST	-0.0188	0.0632	0.2367***	0.1824***	0.124	1			
BM	-0.0487	0.0548	-0.577***	0.0568	-0.1516*	-0.0333	1		
ROA	0.1282	0.0412	0.3716***	0.2091***	0.011	0.178**	-0.2146**	1	
Industry_G~e	0.0316	0.0452	0.2472***	0.064	-0.0891	0.016	-0.1595*	0.0574	1

The correlation matrix demonstrates substantial relationships among critical variables, providing a comprehensive understanding of the ways in which various factors affect the value of a firm. The presence of an inventor CEO (0.2526***), R&D intensity (0.3697***), capital expenditure intensity (0.2367***), and return on assets (0.3716***) are all positively correlated with Tobin's Q, a measure of market valuation. This implies that the market perceives firms led by Inventor CEOs as more innovative and valuable, which is consistent with real-world trends in which a higher market valuation is frequently associated with leadership in innovation. For instance, organisations such as Tesla and Nvidia, which are managed by CEOs who are inventors, frequently achieve elevated market valuations as a result of their substantial R&D investments and innovative strategies.

Tobin's Q (-0.5770***) exhibits a robust negative correlation with the book-to-market ratio (BM), suggesting that firms with higher market valuations have lower book-to-market ratios. Amazon and Google, which are highly valued by the market due to their anticipated future growth, maintain low book-to-market ratios. This relationship is consistent with market behaviour witnessed in high-growth sectors, such as technology. This inverse relationship is indicative of investor expectations that firms with substantial growth potential and innovation capabilities will continue to outperform, resulting in higher market valuations than their book values.

Finally, the substantial influence of macroeconomic conditions on firm valuations is underscored by the positive correlation between the industry growth rate and Tobin's Q (0.2472***). Companies that operate in industries that are experiencing accelerated growth, such as renewable energy or technology, frequently experience elevated market valuations. For example, the renewable energy sector has experienced a rise in market valuations as a result of global initiatives to achieve carbon neutrality and sustainability. This correlation emphasises the significance of industry dynamics in the formation of investor perceptions and firm value. The Variance Inflation Factor (VIF) analysis confirms that multicollinearity is not a concern, thereby guaranteeing the robustness and reliability of these relationships for subsequent analysis.

Variable	**VIF**
const	6.13581
INV_CEO	1.088908
R&D /AST	1.056212
CAPX/AST	1.072858
BM	1.121212
ROA	1.129581
Industry_Growth_Rate	1.046733

Table 4. (VIF) of Table 3

4.1 Traditional Regression

Table 5 regression results provide insights into the impact of various factors on Tobin's Q, a measure of firm value. The results from the fixed effects model are presented below, with key metrics and coefficients highlighted.

TOBINS_Q	**Coefficient**	**Std. err.**	**P>z**
INV_CEO	0.2642928	0.1242867	0.033
RD/AST	2.942398	0.5045935	0
CAPX/AST	0.7839102	0.9168181	0.393
BM	-1.449381	0.1743783	0
ROA	0.5040725	0.1413058	0
Industry_Growth_Rate	1.977455	0.4357497	0
_cons	1.437684	0.096855	0
R-squared	0.5556		
Obs	150		

The regression analysis clarifies the crucial factors that determine the value of a corporation, as assessed by Tobin's Q, within the framework of economic theory and corporate finance. Significantly, having a CEO who is an inventor (coefficient = 0.2643, p = 0.033) noticeably increases the market value. This discovery is consistent with Schumpeter's theory of creative destruction, which states that inventive leadership is responsible for driving technological progress and causing upheavals in the market (Schumpeter, 1942). The congruence with empirical facts indicates that companies managed by visionary CEOs, especially those with patents, frequently surpass the market because of their innovative abilities and forward-looking tactics (Holmstrom, 1989).

Furthermore, the significant and positive effect of R&D intensity (coefficient = 2.9424, p < 0.0001) on Tobin's Q highlights the crucial importance of innovation in endogenous growth theory. Romer (1990) argues that investments in research and development (R&D) are crucial for advancing technology and fostering economic growth. The substantial coefficient suggests that companies who make substantial investments in research and development (R&D) are able to generate a significant amount of intellectual capital. This, in turn, improves their potential for future earnings and allows them to have higher market valuations. The resource-based view theory, as proposed by (Barney, 1991) reinforces this observation by stating that distinct resources possessed by a company, such as exclusive technology, are crucial for attaining long-lasting competitive advantage.

Moreover, the return on assets (ROA) coefficient of 0.5041, with a p-value less than 0.0001, shows a positive correlation with Tobin's Q indicating the effectiveness of enterprises in converting their assets into earnings. The importance of operational efficiency in corporate finance is highlighted by this link, as effective asset management is crucial for maximising shareholder value (Jensen, 1986). On the other hand, there is a strong and statistically significant negative correlation between the book-to-market ratio (BM) (coefficient = -1.4494, p < 0.0001) and Tobin's Q. This suggests that companies with higher market valuations generally have lower BM ratios. This aligns with the principles of value theory, which propose that lower BM ratios indicate companies that own significant intangible assets and prospects for growth (Fama & French, 1992).

Furthermore, the coefficient of the industry growth rate (1.9775) has a highly substantial positive impact on Tobin's Q, highlighting the crucial role of macroeconomic conditions and industry dynamics in influencing the performance of firms. Companies participating in fast expanding sectors experience advantageous market conditions, resulting in increased valuations (Porter, 1980). The model's resilience, demonstrated by high R-squared values and a large Wald chi-squared statistic, guarantees dependable insights for strategic financial management and policy creation. These findings emphasise the crucial significance of forward-thinking leadership, investment in research and development, effective operational practices, and favourable conditions within the industry in order to increase the value of a company.

4.2 Machine Learning Regressions

4.3 Gaussian Process Regression

The Gaussian Process Regression (GPR) model obtained a Root Mean Square Error (RMSE) of 0.2454, suggesting a good level of predicted accuracy. This figure shows a tiny average departure from the real Tobin's Q values. The MSE of 0.0602 provides additional evidence by representing the average of the squared discrepancies between predicted and actual values, demonstrating the model's effective error reduction capability. Furthermore, the R-Squared value of 0.7684 indicates that the GPR model accounts for approximately 76.84% of the variation in Tobin's Q, highlighting its robust explanatory capability. The Mean Absolute Error (MAE) of 0.1759 indicates that the model's predictions have a low average magnitude of errors, thereby verifying the precision of the model.

Model Type	RMSE (Validation)	MSE (Validation)	RSquared (Validation)	MAE (Validation)
Gaussian Process Regression	0.245359578	0.060201322	0.768375345	0.175919768
Ensemble	0.258929859	0.067044672	0.742045551	0.185740152
Neural Network	0.350125044	0.122587546	0.52834428	0.239728531
SVM	0.678220975	0.459983691	-0.769787763	0.300882907

Table 5 machine learning results

Gaussian Process Regression (GPR) is a non-parametric Bayesian approach that constructs a probabilistic model over functions, allowing for flexible modelling of complex relationships. It provides point estimates and confidence intervals, crucial for understanding uncertainty in predictions and making informed decisions. Common kernels include RBF, Matérn, and periodic kernels (Carl Edward Rasmussen & Williams, 2005). Although GPR has notable benefits such as efficient handling of tiny datasets and the capacity to quantify uncertainty, it requires large processing resources. The need to calculate the inverse of the covariance matrix, which increases in complexity as the number of data points cubed, presents difficulties when dealing with larger datasets. Due to this computational complexity, it is important to carefully assess the balance between the flexibility of the model and its viability in terms of computation. In addition, GPR necessitates careful hyperparameter optimisation, namely in the selection of the suitable kernel and its parameters, in order to achieve optimal performance. Although faced with these difficulties, the strong performance of GPR in this study, as demonstrated by its better RMSE, R-Squared, and MAE metrics, reveals its effectiveness in capturing the intricate connections within the data. This makes it an extremely appropriate model for forecasting Tobin's Q in financial analysis.

4.4 Ensemble Learning

The Ensemble Learning model had robust predictive capabilities for Tobin's Q, as indicated by its validation metrics: an RMSE of 0.2589, MSE of 0.0670, R-Squared of 0.7420, and MAE of 0.1857. The metrics demonstrate that the ensemble model obtained a high level of predicted accuracy, with a minimal average deviation from the actual values. Additionally, the model was able to explain around 74.20% of the variance in Tobin's Q. The low mean absolute error (MAE) further validates the accuracy of the model's predictions, establishing it as a reliable option for this regression assignment. Ensemble Learning enhances predictive accuracy by amalgamating numerous base models, thereby capitalising on their particular strengths and alleviating their flaws (Dietterich, 2000). The dataset used in this study consists of intricate interactions and non-linear correlations that are commonly found in financial analysis. The capacity of Ensemble Learning to incorporate various model views enables it to capture these intricacies more completely than individual models. This methodology guarantees the durability of the predictive model over various subsets of data, as seen by the high R-Squared value and low error metrics. Therefore, the practical implementation of the ensemble technique in this particular situation emphasises its superiority in dealing with the variability and multi-dimensionality of financial data, resulting in more dependable and precise estimates of Tobin's Q.

4.5 Neural Networks

Neural networks are renowned for their capacity to represent intricate, non-linear connections within data as a result of their hierarchical arrangement and their ability to learn through backpropagation (LeCun, Bengio, & Hinton, 2015). These models are well-suited for datasets with complex relationships, as they have the ability to adjust and acquire knowledge from the data in order to detect subtle patterns. The model demonstrated a moderate level of effectiveness in forecasting Tobin's Q. The Root Mean Squared Error (RMSE) was 0.3501, indicating a comparatively larger average divergence between the predicted values and the actual values when compared to other models such as Gaussian Process Regression and Ensemble Learning. The higher root mean square error (RMSE) value suggests that the model's predictions were less precise, indicating a higher level of variability in the errors made throughout the forecasts. Furthermore, the Mean Squared Error (MSE) was calculated to be 0.1226, indicating a significant disparity between the anticipated and actual values in terms of their average squared differences.

The R-Squared value of 0.5283 for the coefficient of determination suggests that the Neural Network model can account for roughly 52.83% of the variability in Tobin's Q. This implies that although the model is able to capture certain fundamental patterns in the data, it fails to explain about half of the variation. The Mean Absolute Error (MAE) of 0.2397 indicates a relatively larger average magnitude of errors in the predictions, highlighting the model's modest precision.

4.6 Support Vector Machines (SVM)

For transparency, the (SVM) model exhibited inferior performance in forecasting Tobin's Q, as evidenced by multiple crucial indicators. The Root Mean Squared Error (RMSE) was observed to be 0.6782, which indicates a substantial average divergence between the predicted values and the actual values. The large root mean square error (RMSE) indicates significant variability in the prediction errors, indicating that the model has difficulty accurately forecasting Tobin's Q. Furthermore, the Mean

Squared Error (MSE) was calculated to be 0.4600, emphasising the significant average squared discrepancies between the anticipated and actual values. The model has an R-Squared value of -0.7698, indicating that its performance was inferior to that of a basic mean predictor. The R-Squared value being negative suggests that the model was not successful in accurately representing the variation in Tobin's Q. In addition, the Mean Absolute Error (MAE) was 0.3009, indicating a larger average magnitude of prediction mistakes, further indicating the model's lack of precision and reliability.

Support Vector Machines (SVMs) are highly successful in areas with a large number of dimensions. They are especially useful when the number of dimensions is more than the number of samples, (see Cortes and Vapnik,1995). Kernel functions, such as polynomial, radial basis function (RBF), and sigmoid kernels, can be employed to represent non-linear connections in modelling. Nevertheless, the underwhelming performance of the SVM model in this investigation indicates possible problems such as inadequate optimisation of hyperparameters or an unsuitable selection of kernel. The elevated RMSE and MAE values, along with the unfavourable negative R-Squared, suggest that the SVM model was inadequate in capturing the fundamental connections within the data. This indicates that the model may have either too fit or insufficiently suited the data, resulting in ineffective generalisation.

Chapter 5

5.0 Conclusion & Future Research

5.1 Summary of Key Findings

The objective of this investigation was to determine whether inventor CEOs have a beneficial effect on the value of their organisations. By utilising a variety of machine learning models. Our results demonstrated that firms with CEOs who are inventors tend to have higher Tobin's Q values, which suggests a positive effect on firm value. It is important to note that the GPR and Ensemble Learning models were able to accurately predict the complex and non-linear relationships present in the data.

The machine learning models exhibited superior performance when contrasted with conventional Ordinary Least Squares (OLS) regression. Although the OLS model was simple and comprehensible, it was unable to adequately account for the non-linearities and interactions in the data, as compared to the machine learning models. The GPR model performed substantially better than the OLS model, which had a higher RMSE and a lower R-Squared, with an RMSE of (0.2454) and an R-Squared of (0.7684). The robustness of these models in analysing the complex dynamics associated with inventor CEOs and firm value was further confirmed by the strong predictive capabilities of Ensemble Learning.

5.2 Limitations

Various constraints were faced throughout this investigation. The main limitation was the small dataset, consisting of just 155 observations, resulting from a change in the research question. This reduced the effectiveness of training more intricate models. In addition, limited time hindered us from doing a more thorough hyperparameter optimisation and model validation. Due to the time constraints of this study, it was not possible to thoroughly investigate all prospective sample firms, variables, and models. These constraints indicate that although the results are strong, they would benefit from additional confirmation using a larger dataset and a longer period of analysis.

5.3 Future research Directions

To further build on the findings of this study and address its limitations future research should explore avenues to enhance understanding of the impact of founder CEOs, on company value. One promising area for exploration involves using artificial intelligence to assess media sentiment. Analysing media sentiment can offer insights into how the market perceives CEOs and their effect on company value. By incorporating media sentiment as a mediator researchers can capture nuances in opinion and their influence on performance. This approach can enhance models ability to elucidate investor behaviour by taking into account the behavioural factors that shape it. Positive media coverage of a CEOs groundbreaking initiatives can boost investor confidence resulting in an uptick in the firms market value. Conversely a negative outlook could erode investor trust. Have implications for the company’s value. Integrating media sentiment analysis, into the modelling framework could yield a understanding of how external perspectives impact financial outcomes.

In the realm of research, it is vital to expand the dataset by including observations. Enlarging the dataset would enable the training of models that can better capture the relationships between variables. By gathering data researchers can improve the applicability of their findings ensuring results that can be applied across different scenarios and timeframes. Larger datasets also facilitate the use of validation techniques like cross validation which help prevent overfitting and optimize model performance on data. Moreover, there is a need to explore machine learning methods such as learning models and hybrid approaches that combine different algorithms. Deep learning models have the ability to extract patterns and connections from datasets revealing intricate insights that traditional models might miss. Integrating machine learning techniques in strategies leverages the strengths of each method leading to improved predictive accuracy and model resilience. Future investigations could identify the models, for accurately assessing how innovative leadership impacts financial success by experimenting with a diverse array of machine learning approaches.

To summarise, future study should integrate media sentiment analysis, broaden datasets, and investigate advanced machine learning approaches in order to enhance the current findings and overcome any existing restrictions. These methodologies will offer more profound understanding of the influence of inventor CEOs on the value of a company and enhance the strength and comprehensiveness of financial models.

5.4 Recommendation

Based on the findings of this research there are recommendations that can be offered to investors, scholars, and the business community regarding the impact of CEOs who're also inventors, on a company’s worth. Investors should carefully assess both the benefits and drawbacks of companies led by CEOs taking into account the entire management team, strategic direction and performance metrics to make well informed investment decisions. Scholars are encouraged to delve into this topic by incorporating variables like media perception and market dynamics expanding the range of data collected and utilizing advanced machine learning techniques for more reliable and widely applicable results. Studying this phenomenon over time can offer insights, into how CEOs influence businesses in different market environments.

Corporate entities should acknowledge the potential benefits of appointing a CEO who is an inventor and cultivate an environment that promotes creativity and originality, while also maintaining a prudent approach to financial and operational management. It is essential to comprehend the influence of media mood and investor views on the value of a company and to proactively handle public relations and investor communications initiatives. By taking into account these suggestions, investors, scholars, and business managers can effectively exploit the potential influence of inventor CEOs, resulting in more knowledgeable choices and tactics in their respective domains.

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