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Addressing the Marketing-Finance Interface through Stakeholder Risk: A Machine Learning Approach

Author: M.F. Haasjes
Student number: 543551
Thesis supervisor: Dr. L. Gemmer
Second reader: [tba]
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PREFACE AND ACKNOWLEDGEMETS

This paper extends the marketing-finance interface within the context of the Stakeholder Risk. Its principal objective is to find empirical evidence for the accountability of marketing investments and improve Stakeholder Risk prediction. This research undertaking was motivated by enduring conflicts between marketing- and finance departments, especially during budget discussions. Prompting a curious inquiry: “If marketing accountability is improved, will this create mutual understanding with finance?” The scope of the research is to improve the accountability of the marketing department based on a shared risk in the US market.

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ABSTRACT

Over the years, marketing investments have been perceived as less impactful, particularly by finance departments. Marketing managers often need help with measuring the effectiveness of their investments. Additionally, the marketing- and finance managers use different tools to measure the effectiveness of an investment. Marketing departments focus on customers, while finance departments focus on shareholders. These differences lead to conflicts within the organization. Within this context, the core purpose of this paper is to investigate the accountability of marketing based on Stakeholder Risk and to improve Stakeholder Risk predictions based on S&P 500 data. This analysis reveals that evidence fails to conclude that marketing tools significantly lower the Stakeholder Risk in the same year. However, lagged marketing effects were observed three years after the investment. The introduction of the random forest improves predictions of the Stakeholder Risk. Management can improve marketing accountability by focusing on the lagged effects of at least three years.

Keywords: Marketing-Finance Interface, Stakeholder Risk, S&P 500, Random Forest Model, US Market.

JEL Classification: C23, C45, D25, D81 & M31.

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1. Introduction

Both marketing and finance are disciplines derived from the 'mother' economics. However, the economic roots of marketing are sometimes forgotten (Zinkhan & Verbruge, 2000). The marketing domain is full of creative minds, yet there is a notable scarcity of individuals who favor an analytical approach to the domain (McGovern et al., 2004). People often see marketing and finance as two different worlds, which sometimes prescribe divergent solutions and recommendations to top management (Zinkhan & Verbruge, 2000). Different management perspectives of the two disciplines can be the reason for these divergent solutions. Finance managers have a *shareholder approach* and focus on the satisfaction of shareholders by concentrating on resource allocation and asset management. In contrast, marketing managers have a *customer approach* and focus on the identification and satisfaction of consumer needs (Zinkhan & Verbruge, 2000). In the paper of Edeling et al. (2021), the authors demonstrate a clear linkage between marketing actions and investor response. However, the driver for long-term viability and survival between the two disciplines has been recognized, due to maximizing customer and shareholder values (de Ruyter & Wetzels, 2000). The difference in focus can lead to contradicting recommendations, for example, with the optimal inventory (Zinkhan & Verbruge, 2000). Finance managers recommend that inventory should be kept at low levels since they concentrate on the efficiency of working capital. High inventory levels will worsen the working capital and, eventually, the firm value. On the other hand, marketing managers will advise higher inventory levels since they focus on demand and sales. Overall, it is important to identify the success factors and barriers to an efficient and effective working relationship between the departments of marketing and finance (de Ruyter & Wetzels, 2000). Of course, both disciplines have an overall goal of increasing the performance of the firm. However, they used both different outcome variables to measure the firm's performance. Finance research examines this by cash flow or the price of the stock, while marketing research measures the firm performance based on variables such as sales, profit, or market share (Zinkhan & Verbruge, 2000; Lovett & MacDonald, 2005).

Companies do not effectively demonstrate marketing accountability, the main issue with the marketing-finance interface (Edeling et al., 2021). There is a need to build a necessary interdisciplinary bridge between finance and accounting research (Edeling et al., 2021). This paper aims to bridge the gap between marketing and finance research by making marketing

metrics accountable with the help of the stakeholder risk approach using machine learning methods. As stated in the paper of Edeling et al. (2021, p. 873): "*Further research is necessary on emerging risks that capture stakeholder attention and lead to brand devaluation, cash flow volatility and firm risk, and attendant firm-value drawdowns*. " The stakeholder risk is the risk in interactions between a business and the various groups or individuals capable of influencing (Parmar et al., 2010). In this paper, the *Stakeholder Risk approach* will be a combined risk measured by marketing and financial risks. The marketing risks will focus on brand devaluation, while the financial risks will focus on cash and firm risks. In the paper of Edeling et al. (2021, p. 873), they suggest using natural language processing in future research: "*Future research could use natural language processing, such as random forest or Naïve Bayes, of publicly available information in company statements*." Besides, previous papers used Stakeholder Risk (e.g., Woolridge et al., 2007; Becchetti et al., 2015); however, none used it for the marketing-finance interface or tried to predict the risk. Based on these gaps in the literature, the research question obtained:

To what extent do marketing metrics influence Stakeholder Risk? Additionally, how can machine learning methods be employed to analyze and predict the impact of these marketing metrics on stakeholder risk in the US?

Answering this research question provides relevant insights for the marketing-finance interface literature since it can lower the gap between performance measurement differences. Instead of marketing metrics, which mainly focus on customer-based dependent variables, and financial metrics, which mainly focus on shareholder/investor-based dependent variables, this paper provides a shared dependent variable incorporating both marketing and financial dependent variable aspects. Besides, marketing executives face the problem of creation and trade of value, given the evolution of rapidly changing global markets, which has transformed our understanding of effective marketing (Parmar et al., 2010). The effectiveness of marketing will be answered based on this research question.

Creating a shared goal will point marketing and finance managers in the same direction. Freeman (1984) introduced the *stakeholder approach*, which forms the basis of a *Stakeholder Risk*. Daft (2001) used the *stakeholder approach* to measure organizational effectiveness. This shared goal can lower the rivalry between the disciplines since they have a shared goal and depend on each other. In other words, they must work together to achieve their goal. Next, this

analysis reviews marketing and finance and their importance on each other's outcome variables. For example, marketing may understand the importance of financial metrics when measuring *Customer Risk*, while finance may understand the importance of marketing metrics when measuring *Shareholder Risk*. This mutual understanding can improve marketing productivity since marketing managers can measure the effectiveness of their investments correctly (Verhoef & Leeflang, 2010).

Important to note is that the variables used in this dataset are published in the companies' annual reports. Based on this research question, short-term marketing effects on stakeholder risk cannot be measured.

The paper is structured as follows. Firstly, section 2 provides the theoretical background and literature review. This section presents the theory behind the stakeholder theory and the main previous findings of the marketing-finance interface. Secondly, section 3 discusses the hypotheses. This section presents the hypothesis used in the paper's analysis by providing relevant literature. This section also presents the theoretical framework of the model. Thirdly, section 4 discusses the empirical analysis of the paper. This section will describe the descriptives and statistics of the data set, the calculation of the *Stakeholder Risk*, and the methods used for the regression with time- and firm-fixed effects and the random forest. Fourthly, section 5 provides the empirical findings of the research. This section will discuss and evaluate the hypotheses based on the results and robustness tests. The following section, section 6, provides a discussion of the results. This section discusses the results and opens the debate for some limitations and avenues for future research. Lastly, section 7 provides the conclusion. This section answers the main research question.

2. Theoretical Background and Literature Review

This section is divided into two subsections. The first subsection provides the theoretical background of this paper, and the second subsection provides a literature review of previous research.

2.a. Theoretical Background

The stakeholder theory was first introduced by Freeman (1984). The goal of this approach was to tackle three interconnected problems:

1. The problem of value creation and trade:
   Questioning how value is created and traded in a global and changing business context.
2. The problem of the ethics of capitalism:
   Questioning what the connections are between ethics and capitalism.
3. The problem of managerial mindset:
   Questioning how managers should think of management. Addressing better value creation or explicitly focusing on the connection between ethics and business (Parmar et al., 2010).

Stakeholder theory proposes that by focusing on the interactions between a business and the various groups or individuals capable of influencing, we enhance our ability to deal with these three challenges effectively (Parmar et al., 2010). From a stakeholder perspective, business is understood as a set of interactions, or better said relationships, between groups that have a stake in the business's operations (Freeman, 1984). In other words, communities and managers (e.g., customers, suppliers, financiers) work together to create and exchange value (Parmar et al., 2010). As mentioned in the introduction, interests between stakeholders may conflict. For example, focusing only on customer satisfaction and leaving important financials out is a business that is or will be declining—overemphasizing the consumption markets results in weakened stock price performance (Lovett & MacDonald, 2005).

Another example is a business that focuses on its financials and leaves out the drivers of their profits, the customers. It is a business that is or will be in decline—overemphasizing the financial market results in a focus on promoting the company to its investors while not materializing the delivery of products or services, resulting in a (negative) revaluation of investors' expectations, causing stock price corrections (Lovett & MacDonald, 2005).

Executives should manage these relationships since this will create more value and help the business survive (Parmar et al., 2010). It also represents a moral undertaking as it involves considerations of values, decision-making, and the potential consequences for a broad array of groups and individuals (Phillips, 2003).

However, in traditional finance scholars, the *stakeholder theory* is often ignored (Parmar et al., 2010). In Zingales's paper (2000), the author argues that corporate finance theory needs to be updated since it describes the firm as a web of investments built around a valuable resource. Nonetheless, nonfinancial stakeholders influence the finances of the firm, such as the debt structure of the firm (Titman, 1984; Istaitieh & Rodriquez-Fernandez, 2006). The primary responsibility/objective is for managers to maximize shareholder value from the financial perspective (Jensen, 2002; Parmar et al., 2010). Jensen (1989) discussed that companies should not neglect stakeholders completely. However, Jensen (1989) argues that companies should prioritize shareholders since they are the only group in the corporation with a long-term interest in its survival. The long-term interest of investors is not entirely correct since investors could easily switch between the firm stocks. Besides, as mentioned before, the investor market is heterogeneous since investors have different time horizons. Next, some customers also have a long-term interest in the firm's survival since they could lose an essential supply source (Parmar et al., 2010). In other words, financial market participants are not the only stakeholders who affect the financial outcomes (Parmar et al., 2010).

Next, marketing, by definition, focuses primarily on the customer relationship (Parmar et al., 2010). Organizations should employ *stakeholder theory* to incorporate a broader range of relationships into a marketing interactions model, leading to increased strategic alternatives for the firm and, consequently, enhanced opportunities to generate value (Polonsky et al., 1999). Compared to financial or behavioral management, marketing typically focuses more on external perspectives. As a result, marketing is well-positioned to address challenges related to monitoring and communicating with external stakeholders (Parmar et al., 2010).

The *stakeholder approach* fosters shared goals and targets. Research shows that shared goals contribute positively to relationship attitude and mutual understanding, thereby reducing conflict between the two departments (Weissbrich et al., 2007). Moreover, different goals may decrease the decision-making process but improve the decision quality due to a broader perspective (Weissbrich et al., 2007).

2.b. Literature Review

The literature review discusses the challenges and opportunities in marketing, its importance, and the marketing-finance interface based on previous research.

2.b.1. Challenges and Opportunities in Marketing

Drivers that improve the influence of marketing within companies are accountability, innovativeness, and customer connections based on Dutch company's data (Verhoef & Leeflang, 2010). The effectiveness of marketing activities is often assumed rather than empirically verified since marketing scholars rarely address the issue of performance or stockholder wealth (Zinkhan & Verbruge, 2000). Compared to the Marketing Score 1999 by Homburg et al. (1999), the influence of marketing declined, especially for marketing decisions such as customer service, pricing, and distribution. More positions are connected to the customers, making marketing less relevant/influential. The connection of more positions to the customers negatively influences the power of other marketing decisions, such as strategy, product development, expansion to foreign markets, and choosing a business partner (Verhoef & Leeflang, 2010). Argued that ineffective marketing strategies have caused more significant damage to shareholder value and possibly more career setbacks than poor accounting practices or questionable financial/fiscal practices have (Verhoef & Leeflang, 2010). Raising the question: Does marketing work? Companies see advertisements as expenses instead of investments (Zinkhan & Verbruge, 2000). Changes in revenue, present in some financial outcome indexes, can be interpreted as punishment by the customers (Porto & Foxall, 2022). Revenues represent the gains obtained from customers, reinforcing the company to maximize its efforts directed toward consumer response (Brown & Revankar, 1971). Marketing is perceived as a cost since marketers find it hard to justify their expenditures (direct) return on investments (Verhoef & Leeflang, 2010). The three consequences are: (1) *Marketing receives less boardroom attention* (Verhoef & Leeflang, 2010). The influence of marketing decisions by the marketing department is 43% out of a survey of 213 participants (Verhoef & Leeflang, 2010), indicating that marketing does not have the overhand in these decisions. This results in marketing having problems placing marketing issues at the center of company strategies (Hanssens & Pauwels, 2016) since marketing receives less boardroom attention. (2) *Marketing is perceived as a cost rather than an investment* (Zinkhan & Verbruge, 2000; Verhoef & Leeflang, 2010). Of course, in a competitive environment, a firm's market share will decline if it cuts its ad budget. However, in a mature oligopoly industry, each competitor will be better

off cutting their advertising budget (Zinkhan & Verbruge, 2000). Consumers in these mature industries are well-informed about the brands and products. Advertisements and promotions have the purpose of letting consumers switch between brands. (3) *The roles of CMOs have become less important than those of CFOs* (Verhoef & Leeflang, 2010). Marketing should achieve greater accountability, requiring a financial behavioral change to achieve more influence within the company (Verhoef & Leeflang, 2010). Besides, many marketers do not measure their investment's short-term or long-term effectiveness due to unwillingness to do so or because they use inappropriate methods or metrics (Verhoef & Leeflang, 2010). Besides, these managers struggle with measuring and interpreting the given results (Verhoef & Leeflang, 2010). The managers' struggle has resulted in a decline in the influence of marketing on corporate life because the success rates of new products and advertisements are low (Verhoef & Leeflang, 2010). The finance literature tests the contribution of marketing activities to overall firm performance through event studies (Zinkhan & Verbruge, 2000). In comparison, most marketing literature contains data about single firms instead of multiple firms (Zinkhan & Verbruge, 2000).

2.b.2. Marketing Importance

Marketing departments should have a vital role within the company since they will improve (in)directly business performance (Verhoef & Leeflang, 2010). The paper of Verhoef & Leeflang (2010) found empirical evidence that companies with a strong market department record higher performance in five of the seven studied countries. A positive relationship between the influence of the marketing department, business performance, and market orientation was evident. Besides, marketing influences financial market measures such as stock prices and return on investment (ROI) through the firm performance in the consumption market (Lovett & MacDonald, 2005). Stocks can be affected by marketing indirectly (e.g., market share and profitability) and directly (e.g., by the perception of investors and analysts) (Lovett & MacDonald, 2005; Edeling et al., 2021; Porto & Foxall, 2022). The business performance is improved because marketing contributes to the long-term cash flow generation due to customer satisfaction (Lukas et al., 2003). When collaborating with finance, marketing should demonstrate the long-term profit stream generated by their investments, such as investments in brand equity. Demonstrating these long-term profit streams can be crucial for securing a solid position within the firm and obtaining resources (Weissbrich et al., 2007). The actual firm performance reflects: *"…the integration of operational efficiency and sales performance, and*

it includes collectively held information that may not be readily measurable or publicly available."(Lovett & MacDonald, 2005, p. 477). In other words, the firm performance is not limited to revenue, market share, profitability, and cashflows.

2.b.3. Marketing-finance interface

Again, strong interdependencies exist between marketing and finance. For example, the marketing-finance interface impacts product investment decisions, brand valuation, and working capital (de Ruyter & Wetzels, 2000). De Ruyter & Wetzels (2000) researched the marketing-finance interface from a relational exchange perspective. Their results show that the departments are more likely to develop a favorable attitude toward each other when they depend more on each other's resources. Besides, they find that inter-functional rivalry, such as budget discussion, negatively influences the relational attitude between the departments. The clash between marketing and other departments is one of the causes of the decline of marketing influence within the company, especially true for solid cooperation with the finance department (Verhoef & Leeflang, 2010). The environment (e.g., socio-economic context) around the manager and the company can encourage or discourage increased investment in marketing, ultimately influencing its effectiveness (Porto & Foxall, 2022). All this may explain why marketing is rarely a priority for company executives (Morvan & Le Gall-Ely, 2021).

Finance departments determine the return on investment (ROI) based on the shareholder value. Financial theory states that the value of the business improves when managers make decisions that increase the discounted value of all future cash flows (Lukas et al., 2003). In financial theory, ROI is an investment's net present value (NPV). The goal is to create shareholder value by generating a positive NPV, indicating a favorable market reaction (Morvan & Le Gall-Ely, 2021). In other words, if the discounted cash generated in the future is higher than the investment, indicating a favorable market reaction. Financial theory discounts the generated cash due to the time value of money; money is worth less in the future than it is today. However, a negative NPV provokes an unfavorable market reaction (Morvan & Le Gall-Ely, 2021).

Marketing fails to consider the importance and implications of the contribution of marketing to shareholder value (Lukas et al., 2003). Besides, the effects of marketing investments are weak for financial outcomes but perform better for predicting market share (Porto & Foxall, 2022). Marketing common objectives are growth in sales, improved market share, and

customer satisfaction (Butterfield, 1999). Unfortunately, these performance indicators can be misleading since the objectives can be counterproductive or have little direct relationship to profitability (Day & Wensley, 1988). Sales may increase or decrease profits but are affected by the operational margins that cover the costs/investments (Lukas et al., 2003). Evidence suggests that marketing actions, such as research and development (R&D), product launch decisions, distribution choices, and promotion plans, influence financial market perceptions (Lovett & MacDonald, 2005). Marketing defines market share improvement under the concept of *economies of scale*, suggesting firms should maximize market share (Lukas et al., 2003). The results of Porto & Foxall's (2022) paper confirm that marketing investments improve market share. The authors found that a one percentage point increase in marketing investments enhances the market share by 0.14 percentage points. However, a one percentage point increase in the previous year's marketing investments leads to a decrease in the marketing share by 0.11 percentage points in the next year, indicating the instability of the effects of the marketing investments (Porto & Foxall, 2022). Unfortunately, the market share outcome is misleading. Lower prices than competitors will increase market share while eroding the firm's margins (Lukas et al., 2003).

The same issue applies to customer satisfaction (Lukas et al., 2003). The best way to satisfy customers is to make, for example, products and services free. However, this will destroy shareholder value since costs will be higher than the returns. Customer satisfaction can conflict, because of this, with the shareholder value orientation (Lukas et al., 2003). Shareholder value is the language in the boardroom that marketers only sometimes speak (Lukas et al., 2003). However, shareholder value does not produce business strategies since it does not address the development of strategies. Marketing can provide these strategies (Lukas et al., 2003).

The investor market is like the customer market, heterogeneous (Lovett & MacDonald, 2005). The time horizons of investors differ. Venture capital companies have a 5- to 7-year investment horizon and focus on value growth potentials (Henderson, 1988). Strategic investors have a long-term investment horizon and are concerned about the firm effectiveness (Lovett & MacDonald, 2005). Turnaround specialists have a short-term horizon and focus on cost-cutting potentials and short-term profitability (Lovett & MacDonald, 2005). Lastly, others, such as banks, focus on tangible assets and cash flow (Lovett & MacDonald, 2005). Besides, the Efficient Market Hypothesis (EMH) acknowledges that investors are not always correct in forecasting the firm’s future returns (Lovett & MacDonald, 2005) due to biases that cause

anomalies (e.g., the overreaction hypothesis, January effect, and day-of-the-week-effect). Financial theory revolves around the Efficient Market Hypothesis (Morvan & Le Gall-Ely, 2021). Markets may be efficient in the sense that they react quickly to information. However, it is harder to assert this efficiency in the long term in setting an unbiased price (Morvan & Le Gall-Ely, 2021). Numerous research studies on the marketing–finance interface have shown the immediate influence of operational marketing actions (e.g., communication and product launches) or strategic marketing moves (e.g., brand buyouts) on stock prices (Changeur, 2004; Wiles et al., 2012; Morvan & Le Gall-Ely, 2021).

Enhanced financial support is achieved when marketing decisions increase transparency, accountability, and information sharing, thereby enhancing the enforceability of these decisions (Weissbrich et al., 2007). Research suggests that a balanced power between marketing and finance may reduce the decision process quality, such as decisions taking longer to achieve consensus. However, this balance also fosters cognitive consideration and improves decision enforceability (Weissbrich et al., 2007). The authors in the paper of Morvan & Le Gall-Ely (2021) argue that an objective of the marketing executive should be communication around the business development plan. Communicating the business development plan enables investors to evaluate the potential for generating future revenues based on the conveyed information. Note that such evaluations are limited to events and do not consider ongoing marketing policies that influence the companies over the long term for corporate valuation (Morvan & Le Gall-Ely, 2021). Financial markets efficiently respond to marketing information, and because of this, finance perceives marketing announcements as being incorporated into stock prices (Hanssens, 2019). The relationship between marketing expenditures and the value of the company is measured by several economic studies. According to these marketing studies, the effect of marketing expenditures is:

1. An increase in shareholders returns (Rao & Bharadwaj, 2008),
2. A decrease in working capital requirements (Rao & Bharadwaj, 2008),
3. A reduction of the volatility in the firms' operational flows (Larking, 2013; Fornell et al., 2016),
4. An improvement of the financial- and credit ratings (Larking, 2013; Fischer & Himme, 2017),
5. A reduction in the costs of debt (Fornell et al., 2016),
6. An improvement of the firm value (Du & Osmonbekov, 2020),

7. An improvement in the investors' attention (Morvan & Le Gall-Ely, 2021),
8. An improvement of the company's shares indirectly (Lovett & MacDonald, 2005; Edeling et al., 2021; Porto & Foxall, 2022),
9. Enhanced visibility of the company's NPV and decreased cash requirements (Porto & Foxall, 2022).

On the other hand, finance literature produces mixed results about the effect of marketing. In the paper of Core et al. (2003), the authors did not find a significant impact on company value caused by marketing spending. Currim et al. (2012) explained that marketing expenditures impact profits negatively in the short term (the progress year) while contributing positively in the long term. The authors argue that myopic managers—who have a short-term incentive—reject long-term investments.

Some papers have observed interaction effects between marketing and debt. For instance, the authors in the paper of Malsche & Agarwal (2015) noted a negative relationship between consumer satisfaction and the level of debt. Debt levels can reduce a company's spending, such as on advertising and R&D, which can indirectly affect consumer satisfaction, especially for companies operating in a competitive environment. However, in the paper of Fischer & Himme (2017), the authors found a positive relationship between brand capital and credit rating. The healthier the brand capital, the easier a company can raise financing, which can improve the financial resources for marketing. Enhanced resources for marketing can improve brand capital, contributing positively to the company's credit rating and long-term profitability. In other words, being less at risk enables the company to take on debt under more favorable conditions, reducing the weighted average cost of capital and creating immediate value for shareholders (Morvan & Marine, 2021).

Lastly, cross-functional knowledge (e.g., market knowledge of finance) can increase mutual understanding, decision process quality, and decision enforceability (e.g., finance accepting an increase of marketing budgets due to a better understanding of the investment of marketing activities) (Weissbrich et al., 2007).

3. The Hypotheses

This section will discuss all hypotheses based on their influence on the outcome variable and relevance. This paper uses four different outcome variables (Figure 1). This paper will base these outcome variables on *Customer Risk* or *Shareholder Risk*.

The research question of this paper is "*To what extent do marketing metrics influence stakeholder risk? Additionally, how can machine learning methods be employed to analyze and predict the impact of these marketing metrics on Stakeholder Risk in the US?"* can be split into two main questions. The first question focuses on the initial effect of the marketing metrics on the *Stakeholder Risk*. In contrast, the second question focuses on the prediction of the stakeholder risk with the help of machine learning techniques.

3.a. Marketing metrics and Stakeholder Risk

The hypotheses of *Stakeholder Risk* are divided into *Customer Risk* and *Shareholder Risk*. Logically, if one of the variables does not influence one of the two risks, then it most likely will not influence the *Stakeholder Risk* since the *Stakeholder Risk* is a combination of both.

Customer Risk. The main goal of these hypotheses is to test the influence of the marketing variables on common marketing measurements. *Customer Risk* is divided into volatility in revenue and volatility in gross profit margin (GPM) (Figure 1).

Capital Expenditures (CAPEX) improves the firm's profits and maintains customer value (Firli et al., 2015). The maintenance of customer value indicates that customers tend to be loyal. If the company has loyal customers, then on average, this company will have a more stable revenue stream and profit margin compared to companies with less loyal customers since loyal customers are less sensitive to switching brands/companies. Research by Frederick Reichheld of Bain & Company provides evidence that a 5% increase in customer retention rates improves profits by 25% to 95% (Reichheld, 2001). This stability lowers the risk of extreme fluctuations in the revenue stream and profit margin. Therefore, the following hypothesis emerges:

H1: CAPEX has a negative effect on the Customer Risk.

New product or service developments, facilitated by Research and Development (R&D), play a crucial role in enhancing customer satisfaction. By offering customers something new or improved, R&D can significantly impact customer loyalty (Gremler & Brown, 1999). This loyalty can lead to a ripple effect, with customers persuading others to become regular customers. This, in turn, can lead to stabilized revenue streams and profit margins, thereby reducing the risk associated with customer turnover. This underscores the importance of the following hypothesis:

H2: R&D Expenditures has a negative effect on the Customer Risk.

Customers who are satisfied with the company's products or services will, on average, interact regularly with the company (Gremler & Brown, 1999; Sarkar & Batabyal, 2011). Inventory Turnover can be an indicator of customer satisfaction. In other words, if the Inventory Turnover is high, customers will be satisfied with the products or services and will buy products or services regularly at the company. A high Inventory Turnover means that products are selling quickly and that there is demand in the market. This constant demand indicates that the company sells its products and can lock in a stable revenue stream. This stability in the revenue stream may also indicate a lock in a fixed profit margin. Therefore, the following hypothesis emerges:

H3: Inventory Turnover has a negative positive effect on the Customer Risk.

Advertisements aim to alert customers and push or convince them to purchase. The purchase effect of advertisements contributes positively to the company's revenue streams. The availability of the brand in the consumer's mind creates a purchase effect. Besides, advertisements help generate constant profit margins due to the purchase effect. Advertisements have a carryover effect, the cumulative effect on consumers' brand choice behavior for several years (Mela et al., 1997). Besides, the price sensitivity of consumers may decrease if the advertisement has a nonprice image; however, a price-focused advertisement could increase price sensitivity (Ness, 1977). In other words, the Advertisement Sales ratio (Ad/Sales) may improve the carryover effect and lower price-sensitivity, which lowers the Customer Risk of the company, proposing the following hypothesis:

H4: Ad/Sales has a negative effect on the Customer Risk.

Differentiation strategies build competitive advantage by providing customers with something different or unique compared to the products or services of competitors (Pearce & Robinson, 2016). The competitive advantage built by the differentiation strategy is that customers are more loyal and less price-sensitive to the given product or service (Chege, 2018). Loyal and less price-sensitive customers lower the Customer Risk since they are less likely to search for alternative products or services, which may stabilize the revenue and profit margin of the company. As a result, the following hypothesis is formulated:

H5: Differentiation Strategy has a negative effect on the Customer Risk.

Shareholder Risk. The main goal of these hypotheses is to test the influence of the marketing variables on common financial measurements. The relevance of this is that the inclusion of marketing metrics will provide a better understanding of the contribution of marketing to corporate performance (Lukas et al., 2003). A better understanding of the contribution of marketing to finance can improve their position in the business, improving marketing future budget negotiations (Weissbrich et al., 2007). The *Shareholder Risk* is defined in this paper by the volatility in the earnings per share and the volatility in the operating cash flow.

As mentioned before, CAPEX supports the maintenance of customer value (Firli et al., 2015). A maintained customer value indicates that the customer-firm interaction is stable over time. The effect of this is the company's maintained operating cash flow over time since customers interact on a stable level. Amran & Ali Abdi (2012) found a positive relationship between CAPEX and cash flow. Besides, the satisfaction of customers improves financial performance in the long run (Rechheld, 1996; Schulze et al., 2012; Lee et al., 2015). In other words, this indicates that firms can stabilize their revenues and create relatively stable earnings per share. Hence, the subsequent hypothesis is formulated:

H6: CAPEX has a negative effect on the Shareholder Risk.

R&D, as mentioned previously, improves or maintains customer satisfaction through innovations (Sarkar & Batabyal, 2011). In other words, as cited by Fečiková (2004, p. 57): "*Satisfied customers are more likely to return to those who have helped them, and dissatisfied customers are more likely to go elsewhere next time*." Innovations are products or services created that best fit the customer's needs and improve customer satisfaction. These innovations

may create a competitive advantage since the company offers something competitors can not deliver. Besides, innovations may increase the switching cost: the cost a customer pays when changing brands, products, or services. Both indicate that customers are less likely to switch brands. Innovations and high switching costs create long-term customer satisfaction, improving financial performance in the long run (Rechheld, 1996; Schulze et al., 2012; Lee et al., 2015). In the long run, operating cash flows and earnings per share can stabilize since a relatively constant amount of customers support interacting with the company. Consequently, the ensuing hypothesis is introduced:

H7: R&D Expenditures has a negative effect on the Shareholder Risk.

Inventory Turnover is an indicator of customer satisfaction. A high Inventory Turnover indicates that the company can sell its products or services promptly (Gremler & Brown, 1999; Sarkar & Batabyal, 2011). As mentioned before, the more satisfied customers are, the more loyal the customers will be, and the more often customers interact with the company. Customer satisfaction and loyalty may indicate that the operating cash flows and earnings per share are stable over time, reducing the Shareholder Risk. The stability can be explained by improved financial performance in the long run due to consumer satisfaction (Rechheld, 1996; Schulze et al., 2012; Lee et al., 2015). As a result, the follwing hypothesis can be formulated:

H8: Inventory Turnover has a negative effect on the Shareholder Risk.

Advertisements attract potential and existing customers from the market by creating brand awareness (Chang & Chang, 2014). Brand awareness is customers' capability to recall and memorize brand information (Romaniuk et al., 2017). Advertisements may push customers into a purchase of their products, sometimes without customers realizing it. For example, Coca-Cola has marked its brand in the minds of its customers. If people want to order Coke in a restaurant, they order a Coca-Cola instead of just a Coke. The waitstaff even apologized to Pepsi Coke if Coca-Cola was not available. This example, shows that advertisements can mark brands in consumers' minds besides only pushing customers into purchase. Alalwan (2018) found that advertisements positively impact consumer buying intention. The result is that operating cash flows and earnings per share can stabilize since customers keep interacting with the company due to the advertisements. Hence, the following hypothesis is proposed:

H9: Ad/Sales has a negative effect on the Shareholder Risk.

As mentioned, the Differentiation Strategy creates a competitive advantage (Pearce & Robinson, 2016), customer loyalty, and less price-sensitive customers (Chege, 2018). Loyal customers create customer capital since they have a good relationship with the company. A good customer capital has a positive effect on a company's financial performance in the long run (Rechheld, 1996; Schulze et al., 2012; Lee et al., 2015). Customers who regularly interact with the company can stabilize operating cash flows and earnings per share, eventually lowering the Shareholder Risk. Hence, the subsequent hypothesis is formulated:

H10: Differentiation Strategy has a negative effect on the Shareholder Risk.

This paper examines hypotheses regression with firm—and time-fixed effects (Section 4, Methods). The hypotheses are not confirmed when the p-value associated with the test statistic is below the significance level and the coefficient is negative. Significant results indicate that the observed results are unlikely to occur due to change.

3.b Machine learning methods and Stakeholder Risk

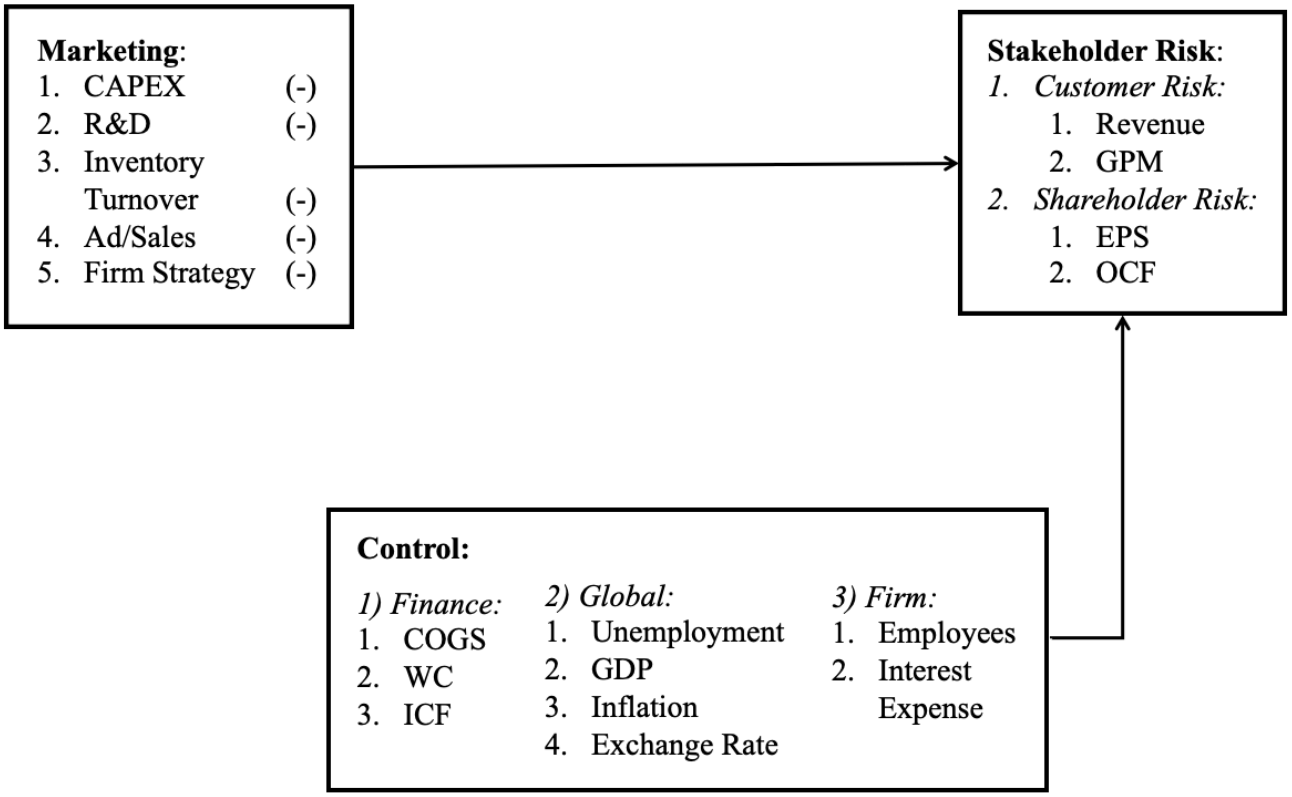
An excellent method to use for prediction purposes is linear regression; however, there are more sophisticated methods that predict more precisely. This paper employs the random forest to enhance the prediction performance of the *Stakeholder Risk*. Random forest models are known for handling complex interactions, high-dimensional data, outliers, and missing data (Zhou et al., 2023). The linear regression assumes linear relationships to predict the outcome variable and is easy to implement and interpret (Zhou et al., 2023). Accurate prediction of the *Stakeholder Risk* may be relevant for companies in the budget allocation. Besides that, relevant predictions in the *Stakeholder Risk* may identify the drivers of this risk, providing management with insights into how to control the *Stakeholder Risk*. Previous research used the *Stakeholder Risk* (e.g., Woolridge et al., 2007; Becchetti et al., 2015); however, it has yet to be used for the marketing-finance interface or tried to predict the risk. Consequently, the following hypothesis is introduced:

H11: The random forest provides more accurate predictions of the Stakeholder Risk than the linear regression.

3.c. Theoretical Framework

Figure 1 provides the theoretical framework of the marketing-finance interface. This framework explains the relationship between the independent- and dependent variables, divided into three domains. (1) Marketing: This domain accounts for all marketing variables. (2) Control: This domain considers the control variables in the model and divides them into three subcategories: (a) Finance, which accounts for the finance variables; (b) Global, which are country (United States) specific economic variables; (c) Firm, these are the firm-specific variables. The control domain accounts for the noise that affects the relationship between the marketing- and finance interface. (3) Stakeholder Risk: This domain contains the dependent variables focused on the *Customer Risk*, the standard marketing outcome variable, and *Shareholder Risk*, the standard finance outcome variable. Marketing raises customer attention to the products or services of the company, which may impact the *Customer*- and *Shareholder Risk* of the company and so on the *Stakeholder Risk*. The control variables may affect the *Stakeholder Risk* per domain differently. Financial decision-making, such as investments, may impact the *Stakeholder Risk through* the *Shareholder Risk*. The Global control variables and economic course variables may affect the *Stakeholder Risk* through the economic well-being of the US. Economic well-being influences the *Stakeholder Risk* through the company's *Customer*- and *Shareholder Risk*. Lastly, the Firm control variables may impact the *Stakeholder Risk* through the company size and interest expense. There may be a difference between small, mid, and large companies. These companies may react very differently on marketing metrics. However, the S&P 500 contains large-capitalization companies (Smith, 2023).

Figure 1. Theoretical Framework - Marketing-Finance Interface



The marketing box contains the independent variables. The control variables are divided into Finance, Global, and Firm subcategories. The dependent variables are in the box of Stakeholder Risk.(-) This sign indicates a negative relationship with the dependent variables. Table 1 explains the short terms in Figure 1.

4. Empirical Analysis

4.a. Data Description

The data is retrieved from CompuStat and Wharton Research Data Service (WRDS). The data contains 481 companies in the Standard & Poor's 500 Index (S&P 500) with a time range from 2000-2022. The total number of observations in this dataset is 10,391. The data focuses on the US market since the S&P 500 considers American-listed companies (Kenton, 2024). One may consider the focus on the US market as a limitation; however, this is necessary for applying an in-debt analysis since the US is the most liquid market. Besides, it is insightful since machine learning methods will be applied, which was omitted in previous research (Edeling et al., 2021). Table 1 presents the overview of the variables used in this paper. Some values are missing, but these missing values (NAs) are randomly disturbed through the dataset. The missing values for Revenue, GPM, EPS, and OCF indicate that quarterly data on these variables were not obtained. Without the quarterly data, it is not possible to measure the volatility, leading to missing values.

1. Data Description Table

Name	Name - Explanation	Type	Unit	Min	Mean	Max	NAs
Ticker	Ticker Symbol.	-	-	-	-	-	-
Company	Company Name.	-	-	-	-	-	-
Year	Fiscal Year.	-	-	-	-	-	-
Revenue	Revenue Volatility[1].	Numeric	Standard Deviation	0	406.94	23,699.27	56
GPM	Gross Profit Margin Volatility.	Numeric	Standard Deviation	0	0.07	7.31	2,012
EPS	Earnings Per Share Volatility.	Numeric	Standard Deviation	0	2.28	14,818.72	179
OCF	Operating Activities net Cash Flow Volatility.	Numeric	Standard Deviation	0	1,231.80	98,699.30	180
CAPEX	Capital Expenditures.	Numeric	USD	-284	1,244.10	77,416	107
COGS	Cost of Goods Sold.	Numeric	USD	-4,310.80	5,149.30	312,077	107
Employees	Number in employees.	Numeric	Employees	0	27,978	2,340,500	107
Interest Expense	Interest Expense.	Numeric	USD	-1,593.40	291.10	37,060.00	107
Unemployment	Unemployment Rate.	Numeric	Percentage	3.61	5.86	9.63	0
GDP	Gross Domestic Product.	Numeric	USD (B^2)	10,250	16,620	27,360	0
Inflation	Inflation Rate.	Numeric	Percentage	-0.40	2.48	8.00	0
WC	Working Captial.	Numeric	USD	-88,590	5,630	482,857	0
Exchange Rate	Exchange Rate Effect.	Numeric	USD	-72,368	-42.22	9,254	0
ICF	Investing Activities - Net Cash Flow.	Numeric	USD	-902,441	-5,788	725,435	0
R&D	Research and Development Expenditures.	Numeric	USD	0	1,123	212,037	0
Inventory Turnover	Inventory Turnover.	Numeric	Ratio	0	4.92	168.93	0
Ad/Sales	Advertising Expenses/Sales Ratio.	Numeric	Ratio	0	0.09	465.69	0
Firm Strategy	Firm Strategy[3].	Binary	-	-	-	-	0

[1] *The volatility) is measured over the quarters of the corresponding year. Besides are the values the other variables yearly.*
[2] *B indicates billion.*
[3] *The Firm's Strategy is marketed as a Differentiation Strategy if the company has Advertisement Expenses; if not, then the company is marketed as a Cost Leader Strategy (McAlister et al., 2016).*

Table 2 visualizes the sector distribution of the firms used in this analysis. The largest portion of these firms are in the *Industrials* and *Financials* sectors, which together account for roughly 30%.

Table 2. Sectors of the Sample Firms

Sectors	**Fraction**
Industrials	15.06%
Financials	14.29%
Information Technology	12.98%
Health Care	12.71%
Consumer Discretionary	12.08%
Consumer Staples	7.42%
Utilities	6.09%
Real Estate	5.84%
Materials	5.49%
Energy	4.19%
Communication Services	3.83%
Total	**100%**

The table defines the fractions of the sectors of the sample firms in the S&P 500.

Table 3 presents the *Pearson* correlation matrix. This correlation matrix measures the strength and direction between two variables, with values ranging from -1 to 1. A negative correlation indicates that variables move in the opposite direction, while a positive direction indicates that variables move in the same direction. A correlation that is close to zero indicates that there is not a linear relationship between the variables. The correlation matrix only considers the (in)dependent numeric variables used in this paper. The correlation between most variables is low. Some variables have a positive moderated correlation (e.g., R&D & Revenue [0.371], Employees & OCF [0.308]). Besides, there is a negative moderated correlation between ICF and OCF [-0.496]. The correlation between R&D and WC [0.645] is relatively high; however, I assume this will not be a problem during the analysis.

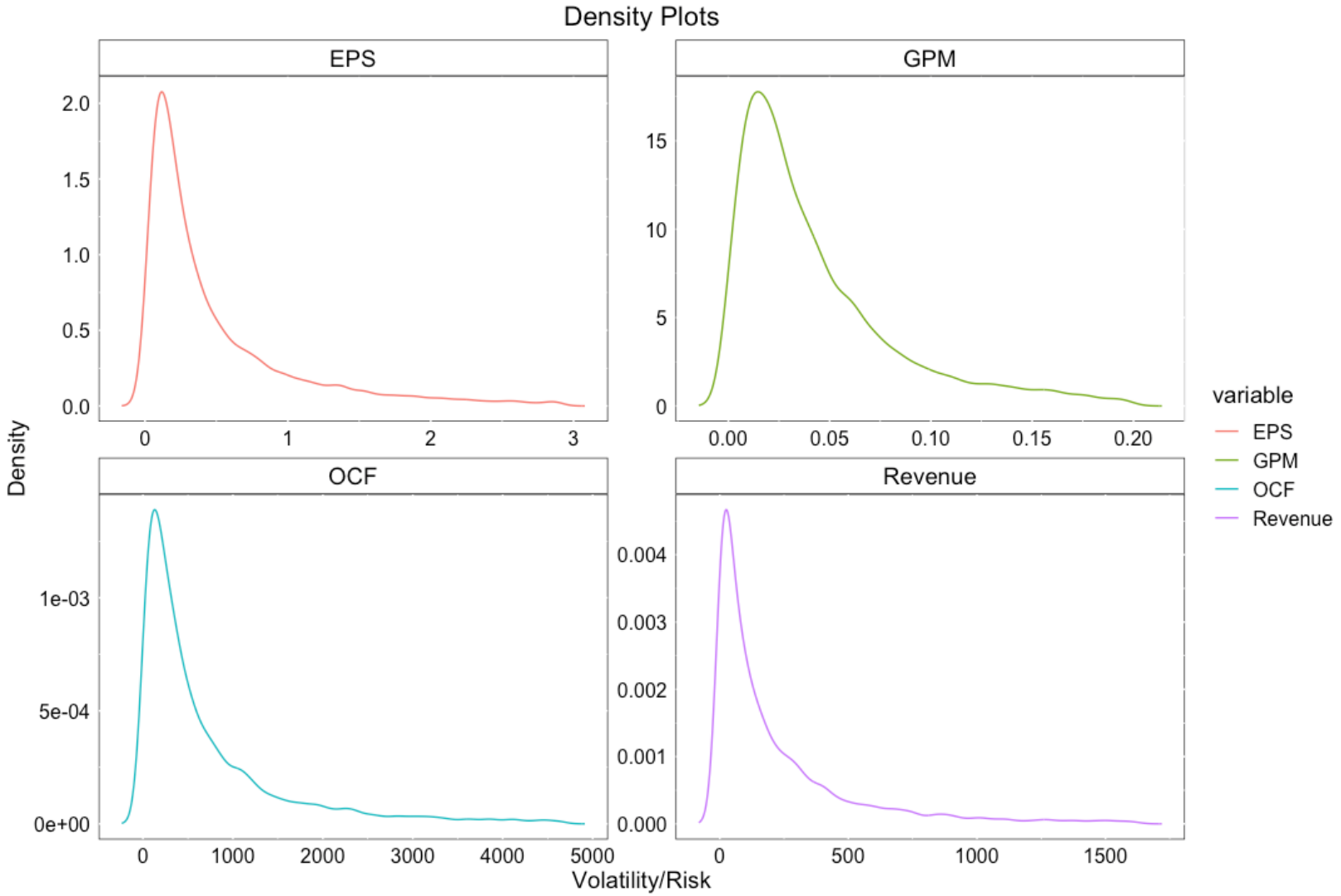
Table 3. Correlation Matrix

	Revenue	GPM	EPS	OCF	CAPEX	COGS	Employees	Interest Expense	Unemployment	GDP	Inflation	WC	Exchange Rate	ICF	R&D	Inventory Turnover	Ad/Sales
Revenue	1																
GPM	0.100	1															
EPS	0.096	0.063	1														
OCF	**0.454**	0.051	0.055	1													
CAPEX	**0.433**	0.043	0.065	**0.336**	1												
COGS	**0.309**	-0.019	0.016	0.120	0.150	1											
Employees	**0.325**	-0.020	0.012	0.194	0.156	**0.308**	1										
Interest Expense	0.248	0.206	0.160	0.188	0.289	0.081	0.123	1									
Unemployment	0.006	-0.026	0.017	0.006	0.013	-0.020	-0.006	0.000	1								
GDP	0.086	-0.075	0.066	0.113	0.058	0.145	0.075	0.009	-0.100	1							
Inflation	0.023	0.046	-0.003	0.005	-0.020	0.003	0.034	-0.002	**-0.357**	0.007	1						
WC	0.193	-0.041	0.032	0.264	0.046	0.087	-0.029	-0.026	0.020	0.091	-0.017	1					
Exchange Rate	-0.035	-0.011	-0.002	-0.201	-0.032	-0.018	-0.075	-0.008	0.009	-0.054	0.000	-0.026	1				
ICF	-0.157	-0.027	0.000	**-0.496**	-0.160	-0.038	-0.089	-0.072	0.012	-0.054	-0.020	-0.061	0.059	1			
R&D	**0.371**	-0.041	0.044	**0.370**	0.197	0.087	0.013	0.049	-0.016	0.104	0.013	**0.645**	-0.035	-0.110	1		
Inventory Turnover	-0.106	-0.056	-0.032	-0.148	-0.102	-0.067	-0.062	-0.113	0.028	-0.061	-0.021	0.175	0.024	0.109	0.064	1	
Ad/Sales	-0.007	-0.001	-0.002	-0.006	-0.006	-0.005	-0.005	-0.004	-0.006	-0.012	0.011	0.000	0.001	0.004	0.002	0.080	1

The numbers marked in bolt show a moderate/high correlation (>0.3).

Figure 2 visualizes the distribution of the dependent variables. The density plot shows that all four dependent variables have a positively skewed distribution since most of the values are clustered around the left tail of the graph, while the right tail is more extended to the right. The positively skewed distribution can also be partly observed from the data description in Table 1 since the maximum values differ significantly from the mean values.

Figure 2. Density Plots



The 5% extreme values are excluded from this plot for each variable.

4.c. Stakeholder Risk

The four dependent variables – Revenue, GPM, EPS, and OCF – are on a different scale. A standard average function, summing up the variables and dividing them by the number of variables, would be inefficient since the *Stakeholder Risk* will be driven by 'extremes' due to the difference in scale. Normalizing the dependent variables on a scale between 0 and 1, using the following formula, solves this inefficiency:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}, \tag{1}$$

where *X'* is the normalized variable, *X* is the variable before normalization, X_{min} is the minimum value of variable *X*, and X_{max} is the maximum value of variable *X*.

The *Stakeholder Risk* is measured with the following arithmetic mean formula:

$$Stakeholder\ Risk = \frac{Customer\ Risk + Shareholder\ Risk}{2}, \tag{2}$$

where the *Customer Risk* exists of the standardized volatility in Revenue and GPM, and the *Shareholder Risk* exists of the standardized volatility in EPS and OCF.

4.b. Methods

This section discusses the methods employed during the analysis. This paper uses two methods: linear regression with firm- and time-fixed effects and the random forest. These methods will be employed to answer the research question. The linear regression is employed to answer the first part of the question: "*To what extent do marketing metrics influence Stakeholder Risk?*". The random forest is employed to answer the second part of the question: "*How can machine learning methods be employed to analyze and predict the impact of these marketing metrics on stakeholder risk in the US?*". The subsection discusses each method on a standalone base.

4.b.1. Linear Regression

The linear regression is employed to answer Hypothesis 1 until Hypothesis 10 (see 3. The Hypotheses). The linear regression will consider firm- and time-fixed effects, allowing the model to eliminate bias from unobservable variables that vary over time but remain constant

across firms while also controlling for the factors that vary across firms but remain constant over time. The computation of firm- and time-fixed effects model is:

$$Y_{it} = \beta_0 + \beta_1 CAPEX_{it} + \beta_2 R\&D_{it} + \beta_3 IT_{it} + \beta_4 Ad/Sales_{it} + \beta_J X_{it} + \nu_{Firm\ Strategy} + \delta_{Year} + \gamma_{Firm} + z_{it}, \quad (3)$$

where $\nu - 1,\ \delta - 1$ & $\gamma - 1$ dummies are included, since the model includes intercept (β_0).

Y_{it}	:	The dependent variable for firm *i* at time *t*,
$CAPEX_{it}$	:	Capital Expenditures for firm *i* at time *t*,
$R\&D_{it}$	:	Research and Development Expenditures for firm *i* at time *t*,
IT_{it}	:	Inventory Turnover for firm *i* at time *t*,
$Ad/Sales_{it}$	:	Advertising Expenses/Sales Ratio for firm *i* at time *t*,
X_{it}	:	The independent control variables for firm *i* at time *t*,
β_J	:	The unobserved parameter vector for the *J*-th independent variable,
$\nu_{Firm\ Strategy}$	:	The coefficient for the specific firm strategy dummy variable,
γ_{Firm}	:	The coefficient for the *n*-th firm-specific dummy variable,
δ_{Year}	:	The coefficient for the *T*-th time-specific dummy variable,
z_{it}	:	The stochastic error term capturing unobserved factors affecting Y_{it}that are not accounted for in this model for firm *i* at time *t*.

The assumption states that the error term has a normal distribution, is not correlated with *x*, and has zero mean. The dependent variables (Y_{it}) used in this model are

1. Volatility in the revenue,
2. Volatility in the gross profit margin (GPM),
3. Volatility in the earnings per share (EPS), and
4. Volatility in the operating cash flow (OCF).

The independent control variables (X_{it}) used in the model are (1) the finance-, (2) the global-, and (3) the firm control variables.

4.b.2. Random Forest

The random forest is a collection of prediction trees $h(x;\theta_k)$. This approach utilizes a machine learning method to answer hypothesis 11. The number of trees is presented by *k* and reach for *k*=1,…, *K*, *x* presents the observed input co-variate vectors of length *p* with associated random vector *X*, and the θ_k are independent and identically distributed (*iid*) random vectors (Segal, 2004). The observed (training) data in the random forest is assumed to be independently drawn from the joint distribution of (X,Y) comprising *n* (*p*+1)-tuples $(x_1, y_1), \dots, (x_n, y_n)$ (Segal, 2004). This paper uses random forest for prediction, defining it by the unweighted average over the collection:

$$h(x) = (\frac{1}{K})\sum_{k=1}^{K} h(x;\theta_k). \quad (4)$$

The number of trees (*K*) can be infinite, the Law of Large Number ensures:

$$E_{X,Y}(Y - \bar{h}(X))^2 \rightarrow E_{X,Y}(Y - E_\theta h(X;\theta))^2. \quad (5)$$

The quantity on the right-hand side is the random forests prediction error designated PE_f^* (Segal, 2004). The convergence depicted in the formula implies that the random forest avoids overfitting. For an individual tree $h(X;\theta)$ the average prediction error is defined as,

$$PE_t^* = E_\theta E_{X,Y}(Y - h(X;\theta))^2. \quad (6)$$

If every θ yields an unbiased tree, i.e. $E_x h(X;\theta)$, then $PE_f^* \leq \bar{\rho} PE_t^*$, where $\bar{\rho}$ represents the weighted correlation between residuals $Y - h(X;\theta)$ and $Y - h(X;\theta')$ for independent θ and θ' (Segal, 2004).

The mean of squared errors (MSE) is used to find the best model by optimizing a random sample m_{try} of predictors. Bagging can be thought of as a particular case of a random forest if the number of $m_{try} = p$, where p is the total number of predictors (Liaw & Wiener, 2002). The MSE of the out-of-bag (OOB) predictions is computed as,

$$MSE_{OOB} = n^{-1}\Sigma_1^n\left(y_i - \hat{y}_i^{OOB}\right), \quad (7)$$

where $\hat{y}_i^{OOB}$ is the average of the out-of-bag (OOB) prediction for the *i*th observation. The out-of-bag data is the validation set for a tree. Following this, the percentage of explained variance is measured as,

$$1 - \frac{MSE_{OOB}}{\sigma_y^2}, \quad (8)$$

where σ_y^2 is computed with *n* as the divisor instead of $n - 1$ (Liaw & Wiener, 2002); lastly, the random forest can measure which variables are the most important in predicting the outcome variable. These most essential variables will be established by assessing their impact on the increase in MSE if the variables are omitted in the tree. It is important to emphasize that this refers to the out-of-bag MSE (OOB-MSE). The increase in MSE is computed as,

$$\%IncMSE_j = \frac{MSE_j - MSE_0}{MSE_0} * 100\%, \quad (9)$$

where *j* represents the *J*-th variable and $\%IncMSE_j$ indicates the percentage increase in MSE for the *J*-th variable. MSE_j is the OOB-MSE if the *J*-th variable is included, and MSE_0 is the baseline error. This baseline error is if the model does not consider any predictor variables. The difference between the two MSE values is averaged across all trees and then normalized by the standard deviation of these differences (Breiman et al., 2022). Put differently, for every tree, each predictor within the out-of-bag (OOB) sample undergoes random permutation and is passed through the tree to generate a MSE. Subsequently, the MSE of the unpermuted OOB sample is subtracted from that of the permuted OOB sample, and this process is averaged across all trees (Soil Survey Staff, 2023).

5. Results

This section discusses the results of the analysis. This section consists of (1) The Customer Risk, (2) The Shareholder Risk, (3) The Stakeholder Risk, (4) Robustness Test of the Stakeholder Risk, (5) Predicting the Stakeholder Risk with Machine Learning, (6) Robustness Test of Predicting the Stakeholder Risk with Machine Learning, and (7) The Hypothesis Conformation Overview.

5.a. The Customer Risk

This subsection focuses on the relevance of marketing variables in predicting *Customer Risk*. Again, the *Customer Risk* contains both Revenue Risk (volatility) and Gross Profit Margin (GPM) Risk (volatility). Before discussing the regression results, note the omission of GDP, Inflation, and Unemployment. This paper focuses on the US, meaning that the GDP, Inflation, and Unemployment do not vary in the corresponding year per firm. In other words, the GDP, Inflation, and Unemployment are already fully covered in the time-fixed effects in the regression. The inclusion of these variables will create singularities.

5.a.1. Revenue Risk

Table 4 provides the regression model estimating the effect of various predictors on Revenue Risk. The data is from an unbalanced panel including 481 firms (n) and covers 2000-2022 (T). The independent variables in the model can explain approximately 27.5% of the variance in Revenue Risk. The F-statistic [114.65] is statistically significant at a 0.1% level, indicating that the overall model does explain a significant portion of the variance in Revenue Risk.

The results show that the marketing coefficients CAPEX and R&D Expenditures significantly affect the determination of Revenue Risk. However, for both variables, the estimates are positive [0.011; 0.093], which indicates that an increase in one of the variables increases the Revenue Risk. In other words, if CAPEX increases by one dollar, the expected Revenue Risk is estimated to increase by 0.011, ceteris paribus. COGS and Interest expense are significant at a 0.1% level and are associated with higher expected Revenue Risk. The financial control variable ICF showed the only significant negative effect. This variable is significant at a 1% level and indicates that a one dollar increase in ICF is estimated to lower the expected Revenue Risk by -0.001, ceteris paribus. Besides, some years appear to be positive and statistically

significant (such as 2007:2009; 2020:2022), which indicates that these corresponding years differ significantly from the baseline year, 2000, based on their impact on the Revenue Risk. Lastly, the firm strategy is a binary, Cost-Leadership- or Differentiation Strategy. The Differentiation Strategy is not statistically significant, which indicates that this strategy does not significantly differ from the Cost-Leadership strategy when predicting the Revenue Risk.

Table 4. Revenue Risk

Coefficients	Estimate	Std. Error	Pr(>|t|)	
2001	25.427	43.695	0.561	
2002	8.395	43.567	0.847	
2003	-2.475	43.241	0.954	
2004	35.189	42.723	0.410	
2005	61.143	42.684	0.152	
2006	36.853	42.555	0.387	
2007	104.370	42.503	0.014	*
2008	278.410	42.470	0.000	***
2009	101.510	42.376	0.017	*
2010	37.966	42.366	0.370	
2011	44.263	42.215	0.294	
2012	28.292	42.148	0.502	
2013	-7.388	42.084	0.861	
2014	59.990	42.065	0.154	
2015	45.630	41.975	0.277	
2016	26.565	41.945	0.527	
2017	25.188	41.966	0.548	
2018	38.954	41.972	0.353	
2019	-11.924	41.899	0.776	
2020	280.290	41.973	0.000	***
2021	161.400	42.082	0.000	***
2022	149.150	43.861	0.001	***
CAPEX	0.011	0.003	0.000	***
COGS	0.010	0.001	0.000	***
Employees	0.000	0.000	0.927	
Interest Expense	0.107	0.007	0.000	***
WC	0.000	0.000	0.298	
Exchange Rate Effect	-0.004	0.007	0.591	
ICF	-0.001	0.000	0.002	**
R&D	0.093	0.002	0.000	***
Inventory Turnover	0.709	1.672	0.671	
Ad/Sales	0.059	1.329	0.964	
Firm Strategy_Differentation	-17.729	33.892	0.601	
R-Squared	28.02%			
Adjusted R-Squared	24.22%			
F-Statistic	114.65		0.000	***
Number of observations	10,234			

*The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1. Note that the baseline year 2000 is removed to prevent perfect multicollinearity.*

5.a.2. Gross Profit Margin Risk

Table 5 provides the regression model, which estimates the effect of various predictors on Gross Profit Margin (GPM) Risk. The data is from an unbalanced panel including 446 firms (n) and covers 2000-2022 (T). The independent variables in the model can explain approximately 9.57% of the variance in GPM Risk. The F-statistic [5.09] is statistically significant at a 0.1% level, indicating that the overall model does explain a significant portion of the variance in GPM Risk.

Time has a significant effect on the GPM Risk. Almost every year in this model (except 2002 and 2019) differs significantly from the baseline year (2000). The inclusion of GDP, Inflation, and Unemployment Rate in the time-fixed effects of this model indicates that these probably have a significant impact on the GPM. However, it is also possible that the years are statistically significant due to other unobserved patterns observed during the years. The Differentiation Strategy seems to lower the GPM Risk compared to a Cost-Leadership Strategy; however, this effect is insignificant. The impact of the other variables tends to be marginal since this model estimates a one-unit increase of variable X. To provide better insights, Table 6 has been created. This table shows the estimates if coefficient *X* is multiplied by 100,000

Table 5. Gross Profit Margin Risk

Coefficients	Estimate	Std. Error	Pr(>|t|)	
2001	0.049	0.013	0.000	***
2002	0.000	0.013	0.975	
2003	-0.064	0.013	0.000	***
2004	-0.074	0.013	0.000	***
2005	-0.068	0.013	0.000	***
2006	-0.074	0.013	0.000	***
2007	-0.033	0.013	0.011	*
2008	0.048	0.013	0.000	***
2009	-0.058	0.013	0.000	***
2010	-0.034	0.013	0.009	**
2011	-0.056	0.013	0.000	***
2012	-0.061	0.013	0.000	***
2013	-0.079	0.013	0.000	***
2014	-0.067	0.013	0.000	***
2015	-0.066	0.013	0.000	***
2016	-0.082	0.013	0.000	***
2017	-0.082	0.013	0.000	***
2018	-0.076	0.013	0.000	***
2019	-0.013	0.013	0.292	
2020	-0.070	0.013	0.000	***
2021	-0.059	0.013	0.000	***
2022	-0.062	0.024	0.010	**
CAPEX	0.000	0.000	0.024	*
COGS	0.000	0.000	0.477	
Employees	0.000	0.000	0.647	
Interest Expense	0.000	0.000	0.000	***
WC	0.000	0.000	0.015	*
Exchange Rate Effect	0.000	0.000	0.129	
ICF	0.000	0.000	0.057	.
R&D	0.000	0.000	0.258	
Inventory Turnover	0.000	0.001	0.567	
Ad/Sales	0.000	0.000	0.796	
Firm Strategy_Differentation	-0.012	0.016	0.472	
R-Squared	9.57%			
Adjusted R-Squared	4.04%			
F-Statistic	25.09		0.000	***
Number of observations	8,306			

*The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1. The baseline year 2000 is removed to prevent perfect multicollinearity.*

Table 6. Gross Profit Margin Risk – Zoom in

Coefficients (x100,000)	Estimate	
CAPEX	0.202	*
COGS	-0.012	
Employees	0.001	
Interest Expense	4.219	***
WC	0.038	*
Exchange Rate Effect	-0.520	
ICF	0.013	.
R&D	-0.090	
Inventory Turnover	29.810	
Ad/Sales	9.537	

*This table is a snapshot of the predictor coefficients in Table 5, multiplied by 100,000. The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1.*

Table 6 makes it possible to observe the magnitude and sign of the variables. For the marketing variables, CAPEX positively affects the GPM Risk, which is significant at a 5% level. If CAPEX increases by 100,000 dollars, the expected GPM Risk is estimated to increase by 0.202, ceteris paribus. The other marketing variables have a positive effect, except R&D Expenditures, on the GPM Risk; however, all these variables are insignificant. Interestingly, interest expense, WC, and ICF significantly positively affect GPM Risk. Based on these results, financial variables are more excellent drivers for the GPM Risk than marketing variables.

The results show that some marketing variables are significant drivers for *Customer Risk*. CAPEX is a significant driver of Revenue- and GPM Risk, while R&D Expenditures is a significant driver of Revenue Risk. However, both variables exhibit a positive effect, suggesting that an increase in either variable is expected to increase volatility/risk, ceteris paribus. A negative influence on *Customer Risk* indicates a lower or more stable level of risk. An increase in the marketing variables does not lower the*Customer Risk*. Some marketing variables even positively impact fluctuations in Customer Risk, indicating an expected uplift in *Customer Risk*. In other words, the results suggest that evidence lacks to confirm that marketing variables have a negative and significant effect on *Customer Risk*.

5. b. The Shareholder Risk

This subsection focuses on the relevance of marketing variables in predicting the *Shareholder Risk*. Marketing departments focus, in general, exclusively on the 'marketing' outcome variables. However, if marketing can show its contribution to classical finance outcome variables, it can improve mutual understanding (Weissbrich et al., 2007). As mentioned before, *Shareholder Risk* exists in Earnings Per Share (EPS) Risk (volatility) and Operating Cash Flow (OCF) Risk (volatility). Before discussing the regression results, it is relevant to note that the variables GDP, Inflation, and Unemployment are excluded due to singularities, as mentioned previously.

5.b.1. Earnings Per Share Risk

The regression model, a crucial tool in estimating the effect of various predictors on Earnings Per Share (EPS) Risk, is presented in Table 7. The data, drawn from an unbalanced panel of 481 firms (n) spanning 2000-2022 (T), reveals that the independent variables in the model can explain approximately 0.43% of the variance in EPS Risk. The non-statistically significant F-statistic [1.27] suggests that the overall model does not account for a significant portion of the variance in EPS Risk. However, the importance of this model in our research cannot be overstated.

Time does not affect the EPS Risk. Only the year 2004 differs significantly from the baseline year (2000). The firm strategies do not vary significantly. However, the Differentiation Strategy negatively affects 8.69 less on the expected EPS Risk than the Cost-Leadership Strategy, ceteris paribus. The magnitude of the non-time variables is marginal since this model estimates a one-unit increase of variable *X*. Table 8 has been created to provide better insights. This table shows the estimates if coefficient *X* is multiplied by 10,000, comparable with Table 6.

Table 7. Earnings Per Share Risk

Coefficients	Estimate	Std. Error	Pr(>|t|)	
2001	0.493	10.793	0.964	
2002	0.894	10.761	0.934	
2003	0.550	10.684	0.959	
2004	34.049	10.548	0.001	**
2005	-1.111	10.510	0.916	
2006	-0.857	10.490	0.935	
2007	-0.626	10.494	0.952	
2008	-0.297	10.465	0.977	
2009	-0.307	10.458	0.977	
2010	-1.026	10.434	0.922	
2011	-1.600	10.431	0.878	
2012	-1.540	10.400	0.882	
2013	-1.497	10.391	0.885	
2014	-1.037	10.367	0.920	
2015	-0.897	10.353	0.931	
2016	-0.537	10.328	0.959	
2017	-0.158	10.342	0.988	
2018	0.407	10.336	0.969	
2019	-0.169	10.316	0.987	
2020	0.087	10.332	0.993	
2021	0.848	10.357	0.935	
2022	7.750	10.822	0.474	
CAPEX	0.000	0.001	0.946	
COGS	0.000	0.000	0.913	
Employees	0.000	0.000	0.913	
Interest Expense	0.000	0.002	0.811	
WC	0.000	0.000	0.806	
Exchange Rate Effect	0.000	0.002	0.944	
ICF	0.000	0.000	0.919	
R&D	0.000	0.001	0.613	
Inventory Turnover	1.795	0.413	0.000	***
Ad/Sales	-0.092	0.325	0.778	
Firm Strategy_Differentation	-8.693	8.500	0.306	
R-Squared	0.43%			
Adjusted R-Squared	-4.89%			
F-Statistic	1.27		0.138	
Number of observations	10,114			

*The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1. The baseline year 2000 is removed to prevent perfect multicollinearity.*

Table 8. Earnings Per Share Risk – Zoom in

Coefficients (x10,000)	Estimate	
CAPEX	-0.508	
COGS	-0.141	
Employees	0.026	
Interest Expense	4.333	
WC	-0.286	
Exchange Rate Effect	1.171	
ICF	0.062	
R&D	2.803	.
Inventory Turnover	17,953.000	***
Ad/Sales	-915.490	

*This table is a snapshot of the predictor coefficients in Table 7, multiplied by 10,000. The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1.*

R&D Expenditures and Inventory Turnover are the only marketing variables significantly affecting the EPS Risk. R&D Expenditures are statistically significant at a 10% level. The interpretation is that if R&D Expenditures increase by 10,000 dollars, the expected EPS Risk is estimated to increase by 2.803, ceteris paribus. Inventory Turnover is statistically significant at a 0.1% level; however, this variable increases the expected EPS Risk. Interestingly, CAPEX and Ad/Sales have a negative effect on the EPS Risk; nonetheless, these variables are insignificant.

5.b.2. Operating Cash Flow Risk

Table 9 provides the regression model estimating the effect of various predictors on Operating Cash Flow (OCF) Risk. The data is from an unbalanced panel including 481 firms (n) and covers 2000-2022 (T). The independent variables in the model can explain approximately 27.51% of the variance in OCF Risk. The F-statistic [110.42] is statistically significant at a 0.1% level, indicating that the overall model does explain a significant portion of the variance in OCF Risk.

Table 9. Operating Cash Flow Risk

Coefficients	Estimate	Std. Error	Pr(>|t|)	
2001	99.026	111.910	0.376	
2002	147.080	111.650	0.188	
2003	157.590	111.280	0.157	
2004	143.220	109.650	0.192	
2005	165.440	109.080	0.129	
2006	403.030	108.980	0.000	***
2007	425.220	108.900	0.000	***
2008	410.240	108.820	0.000	***
2009	447.160	108.580	0.000	***
2010	319.730	108.460	0.003	**
2011	473.120	108.210	0.000	***
2012	330.760	107.980	0.002	**
2013	456.590	107.820	0.000	***
2014	260.010	107.650	0.016	*
2015	320.250	107.340	0.003	**
2016	342.860	107.300	0.001	**
2017	397.580	107.340	0.000	***
2018	522.890	107.290	0.000	***
2019	719.260	107.120	0.000	***
2020	681.090	107.290	0.000	***
2021	746.930	107.550	0.000	***
2022	792.570	112.560	0.000	***
CAPEX	0.043	0.008	0.000	***
COGS	0.012	0.001	0.000	***
Employees	0.001	0.000	0.000	***
Interest Expense	0.100	0.019	0.000	***
WC	0.013	0.001	0.000	***
Exchange Rate Effect	-0.409	0.017	0.000	***
ICF	-0.011	0.001	0.000	***
R&D	0.165	0.006	0.000	***
Inventory Turnover	-2.481	4.314	0.565	
Ad/Sales	1.061	3.372	0.753	
Firm Strategy_Differentation	163.510	89.122	0.067	.
R-Squared	27.51%			
Adjusted R-Squared	23.64%			
F-Statistic	110.42		0.000	***
Number of observations	10,115			

*The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1. The baseline year 2000 is removed to prevent perfect multicollinearity.*

The time substantially impacts the OCF Risk, according to the results in Table 9. 2006 to 2022 differ significantly from the baseline year (2000). The firm's Differentiation Strategy differs significantly from the Cost-Leadership Strategy at a 10% level. Differentiation Strategy has a positive effect of 163.51 more on the expected OCF Risk than the Cost-Leadership Strategy, ceteris paribus, indicating that the Cost-Leadership Strategy lowers the OCF Risk (Table 9). CAPEX and R&D Expenditures have a positive and statistically significant effect on the OCF Risk. The interpretation is that if CAPEX increases by one dollar, the expected OCF Risk is estimated to increase by 0.043, ceteris paribus. The marketing variable Inventory Turnover negatively impacts the OCF Risk; however, this coefficient turned out to be insignificant. Next, the results show that companies with more employees have a higher OCF Risk. Besides, companies with high-interest Expenses have a higher OCF Risk than companies with lower Interest Expenses. The Exchange Rate Effect and ICF contribute statistically significant negatively to the OCF Risk, indicating that an increase in both is expected to lower the OCF Risk, ceteris paribus.

All in all, similar results appeared for the *Shareholder Risk* outcome variables as for the *Customer Risk*. The results show that there is no evidence to conclude that marketing variables tend to lower *Shareholder Risk*. The Cost-Leadership Strategy tends to have a lower OCF Risk than the Differentiation Strategy. Significant marketing variables were observed; however, these variables contributed to a significant increase in *Shareholder Risk*.

5.c. The Stakeholder Risk

This subsection focuses on the relevance of marketing variables in predicting the *Stakeholder Risk*. Marketing departments focus, in general, exclusively on the 'marketing' outcome variables (Butterfield, 1999; Lukas et al., 2003). However, if marketing can show their contribution to a shared outcome variable with finance, it can improve mutual understanding within the company (Weissbrich et al., 2007). As mentioned, the outcome variables – Revenue-, GPM-, EPS-, and OCF Risk – are normalized before measuring the *Stakeholder Risk*. In this regression model, the variables GDP, Inflation, and Unemployment are excluded due to singularities, as mentioned previously.

The regression model's results, presented in Table 10, provide a significant insight into the effect of various predictors on *Stakeholder Risk*. The data, drawn from an unbalanced panel of

446 firms (n) and covering the period 2000-2022 (T), is robust. The independent variables in the model can explain approximately 26.69% of the variance in *Stakeholder Risk*. The F-statistic [85.24] is statistically significant at a 0.1% level, reassuring that the overall model does indeed explain a significant portion of the variance in *Stakeholder Risk*.

The timing effect is prevalent in the *Stakeholder Risk*. Some years (e.g., 2001, 2003, 2004, 2008, 2019:2022) differ significantly from the baseline year (2000). The firm strategies do not vary significantly. The insignificance makes sense since the firm strategy differed insignificantly from almost every previous regression model except the OCF. As was the case for some previous regression, the effect of the other predictor variables has increased the marginal impact on the *Stakeholder Risk for each unit*. Table 11 provides a better overview of the magnitude and direction of these predictor variables.

None of the marketing variables significantly affect the Stakeholder Risk negatively. The significant marketing variables (CAPEX and R&D) positively affect the Stakeholder Risk. The interpretation of CAPEX is that a 1 million dollar increase in CAPEX is associated with a 0.298 standard deviation increase in the normalized *Stakeholder Risk*, ceteris paribus (Table 11). The Exchange Rate Effect and ICF significantly and negatively impact the *Stakeholder Risk*. The number of Employees has a positive and slightly significant effect at a 10% level; however, the magnitude of this effect is marginal.

Table 10. Stakeholder Risk

Coefficients	Estimate	Std. Error	Pr(>|t|)	
2001	0.003	0.001	0.007	**
2002	0.001	0.001	0.375	
2003	-0.002	0.001	0.056	.
2004	-0.002	0.001	0.059	.
2005	-0.001	0.001	0.170	
2006	-0.001	0.001	0.195	
2007	0.001	0.001	0.125	
2008	0.006	0.001	0.000	***
2009	0.001	0.001	0.149	
2010	0.001	0.001	0.409	
2011	0.000	0.001	0.861	
2012	-0.001	0.001	0.421	
2013	-0.001	0.001	0.127	
2014	-0.001	0.001	0.249	
2015	-0.001	0.001	0.514	
2016	-0.001	0.001	0.117	
2017	-0.001	0.001	0.307	
2018	0.000	0.001	0.940	
2019	0.002	0.001	0.052	.
2020	0.004	0.001	0.000	***
2021	0.003	0.001	0.000	***
2022	0.002	0.002	0.277	
CAPEX	0.000	0.000	0.000	***
COGS	0.000	0.000	0.000	***
Employees	0.000	0.000	0.068	.
Interest Expense	0.000	0.000	0.000	***
WC	0.000	0.000	0.000	***
Exchange Rate Effect	0.000	0.000	0.000	***
ICF	0.000	0.000	0.000	***
R&D	0.000	0.000	0.000	***
Inventory Turnover	0.000	0.000	0.464	
Ad/Sales	0.000	0.000	0.816	
Firm Strategy_Differentation	0.000	0.001	0.750	
R-Squared	26.69%			
Adjusted R-Squared	22.09%			
F-Statistic	85.24		0.000	***
Number of observations	8,238			

*The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1. The baseline year 2000 is removed to prevent perfect multicollinearity.*

Table 11. Stakeholder Risk – Zoom in

Coefficients (x1mln)	Estimate	
CAPEX	0.298	***
COGS	0.089	***
Employees	0.003	.
Interest Expense	3.469	***
WC	0.060	***
Exchange Rate Effect	-1.211	***
ICF	-0.024	***
R&D	1.645	***
Inventory Turnover	26.400	
Ad/Sales	5.939	

*This table is a snapshot of the predictor coefficients in Table 10, multiplied by 1 mln. The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1.*

In conclusion, the analysis reveals significant results for the marketing predictor variables. Nonetheless, all these variables are positively associated with *Stakeholder Risk*. The positive association with risk indicates that the results do not provide enough evidence to conclude that the marketing predictor variables lower *Stakeholder Risk*.

5.d. Robustness Test of the Stakeholder Risk

This subsection provides the robustness test of the results from the regression model. As mentioned previously, marketing variables do not significantly negatively affect the Customer-, Shareholder-, and Stakeholder Risk. The insignificant effect can explain the long-term focus of marketing rather than a short-term focus. Marketing investments tend to have a negative impact in the short term; however, they have a positive impact in the long term (Currim et al., 2012). For example, the goal of advertisements can be to not only push customers into a purchase but also to create brand equity. Brand equity is a brand's awareness and a positive association in the consumers' memory (Keller, 1993). Long-term memory accesses internal information, resulting in brand equity paying off in the long term (Keller, 1993). In the previous subsections, the focus was on the short-term effects of the contribution of the marketing expenses to the outcome variables. Again, this short-term focus may not be appropriate for measuring marketing's effectiveness. The focus of this subsection is to test the lagged effects of marketing. The focus will only be on the *Stakeholder Risk* since this captures the *Customer Risk* and the *Shareholder Risk*.

The regression model, which estimates for various predictors the effect on *Stakeholder Risk*, is provided in Table 12. This regression model incorporates lagged effects for marketing, introducing three lags:

1. One year before t=0,
2. Two years before t=0,
3. Three years before t=0.

The data is from an unbalanced panel including 432 firms (n) and covers 2003-2022 (T). It's important to note that 2000-2002 are excluded from the analysis, ensuring that the lagged effects for those years, which are missing in the data, do not affect the results. The independent variables in the model can explain approximately 30.38% of the variance in *Stakeholder Risk*. The explained variance is slightly higher than the model without lagged effects (30.38% > 26.69%). The F-statistic [66.84] is statistically significant at a 0.1% level, indicating that the overall model is statistically significant and does explain a significant portion of the variance in *Stakeholder Risk*.

Table 12. Stakeholder Risk with Lagged Marketing Variables

Coefficients	Estimate	Std. Error	Pr(>|t|)	
2004	0.000	0.001	0.917	
2005	0.000	0.001	0.872	
2006	0.000	0.001	0.787	
2007	0.003	0.001	0.004	**
2008	0.007	0.001	0.000	***
2009	0.002	0.001	0.006	**
2010	0.002	0.001	0.016	*
2011	0.001	0.001	0.106	
2012	0.001	0.001	0.397	
2013	0.000	0.001	0.924	
2014	0.000	0.001	0.614	
2015	0.001	0.001	0.370	
2016	0.000	0.001	0.921	
2017	0.001	0.001	0.555	
2018	0.001	0.001	0.125	
2019	0.003	0.001	0.001	**
2020	0.005	0.001	0.000	***
2021	0.004	0.001	0.000	***
2022	0.003	0.002	0.053	.
CAPEX	0.000	0.000	0.349	
COGS	0.000	0.000	0.000	***
Employees	0.000	0.000	0.225	
Interest Expense	0.000	0.000	0.000	***
WC	0.000	0.000	0.000	***
Exchange Rate Effect	0.000	0.000	0.000	***
ICF	0.000	0.000	0.000	***
R&D	0.000	0.000	0.000	***
Inventory Turnover	0.000	0.000	0.896	
Ad/Sales	0.000	0.000	0.664	
Firm Strategy_Differentation	0.000	0.001	0.725	
CAPEX_lag1	0.000	0.000	0.331	
CAPEX_lag2	0.000	0.000	0.659	
CAPEX_lag3	0.000	0.000	0.001	***
R&D_lag1	0.000	0.000	0.001	**
R&D_lag2	0.000	0.000	0.020	*
R&D_lag3	0.000	0.000	0.002	**
Inventory Turnover_lag1	0.000	0.000	0.780	
Inventory Turnover_lag2	0.000	0.000	0.544	
Inventory Turnover_lag3	0.000	0.000	0.293	
Ad/Sales_lag1	0.000	0.000	0.943	

Ad/Sales_lag2	0.000	0.000	0.892	
Ad/Sales_lag3	0.000	0.000	0.721	
R-Squared	30.38%			
Adjusted R-Squared	25.26%			
F-Statistic	66.84		0.000	***
Number of observations	6,908			

*The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1. The baseline year 2003 is removed to prevent perfect multicollinearity.*

The timing effect is still prevalent after introducing lagged variables (Table 12). Some years (2007:2010, 2019:2022) are statistically different from the baseline year (2003), as shown in Table 12. Note that the significant years differ from the model without lagged effects (Table 10). This difference can be due to the difference in baseline year between the two models. The model without lagged effects has 2000 as the baseline year, while the model with lagged effects has 2003 as the baseline year. Notably, the CAPEX and the number of Employees were significant in the model without lagged effects but were insignificant in the model with lagged effects. The firm strategies are similar to those of the model without lagged effects. The impact of the other predictor variables has, the same as before, a marginal influence on stakeholder risk for each unit increase. Table 13 provides a better overview of the predictor variables' magnitude and sign.

In line with the model without lagged effects, none of the marketing variables have a negative impact if the marketing variable was at t=0. However, CAPEX and R&D have a negative sign and are statistically significant results for a lag of three years. This result indicates that CAPEX and R&D lower the expected *Stakeholder Risk* in the long term, three years after the investment. All lags of the Inventory Turnover and the Ad/Sales are insignificant. Nonetheless, the magnitude of Ad/Sales is the most negative estimate, but the effect is not significant. In other words, the results provide evidence that their marketing variables have a lagged effect on *Stakeholder Risk*.

Table 13. Stakeholder Risk with Lagged Marketing Variables – Zoom in

Coefficients (x1mln)	Estimate	
CAPEX	0.077	
COGS	0.078	***
Employees	0.002	
Interest Expense	4.641	***
WC	0.057	***
Exchange Rate Effect	-1.267	***
ICF	-0.022	***
R&D	1.081	***
Inventory Turnover	-9.717	
Ad/Sales	-131.100	
CAPEX_lag1	0.092	
CAPEX_lag2	0.043	
CAPEX_lag3	-0.294	***
R&D_lag1	0.789	**
R&D_lag2	0.652	*
R&D_lag3	-0.757	**
Inventory Turnover_lag1	24.713	
Inventory Turnover_lag2	-51.304	
Inventory Turnover_lag3	55.968	
Ad/Sales_lag1	21.811	
Ad/Sales_lag2	40.778	
Ad/Sales_lag3	-9.073	

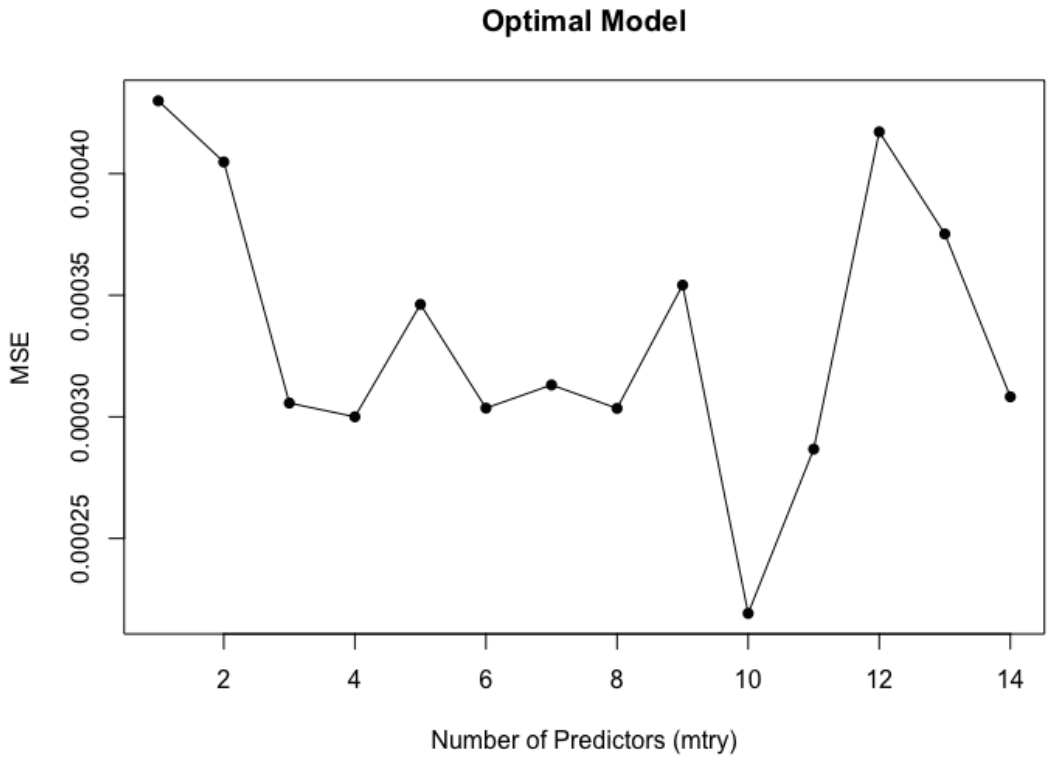
*This table is a snapshot of the predictor coefficients in Table 12, multiplied by 1 mln. The significance levels are 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ' ' 1.*

In conclusion, the model with lagged effects provides evidence for some marketing variables that have a significant negative contribution to the *Stakeholder Risk*. This significant negative contribution may indicate that CAPEX and R&D investments provide customer loyalty. This customer loyalty pays off in the long term through stable *Stakeholder Risk*. This lagged effect aligns with previous research (Keller, 1993; Rechheld, 1996; Lukas et al., 2003; Currim et al., 2012; Schulze et al., 2012; Lee et al., 2015). The risk drivers of this negative effect - revenues, gross profit margins, earnings per share, or operating cash flow - do not infer from this analysis.

5.e. Predicting the Stakeholder Risk with Machine Learning

This subsection predicts the Stakeholder Risk using the random forest model. As mentioned in the methodology, the optimal random sample (*mtry*) of predictors must be selected from the training dataset to find the best model. The optimal *mtry* varies between 1 and the number of predictors (*p*). This parameter randomly samples, at each split, the number of predictors (Breiman et al., 2022). The best model is the model that generates the lowest mean squared error (MSE). The optimal number of predictors is ten, based on a random forest with 500 trees (Figure 3). The MSE of this model is ± 0.00022[4] (Figure 3).

Figure 3. Optimal Number of Predictors

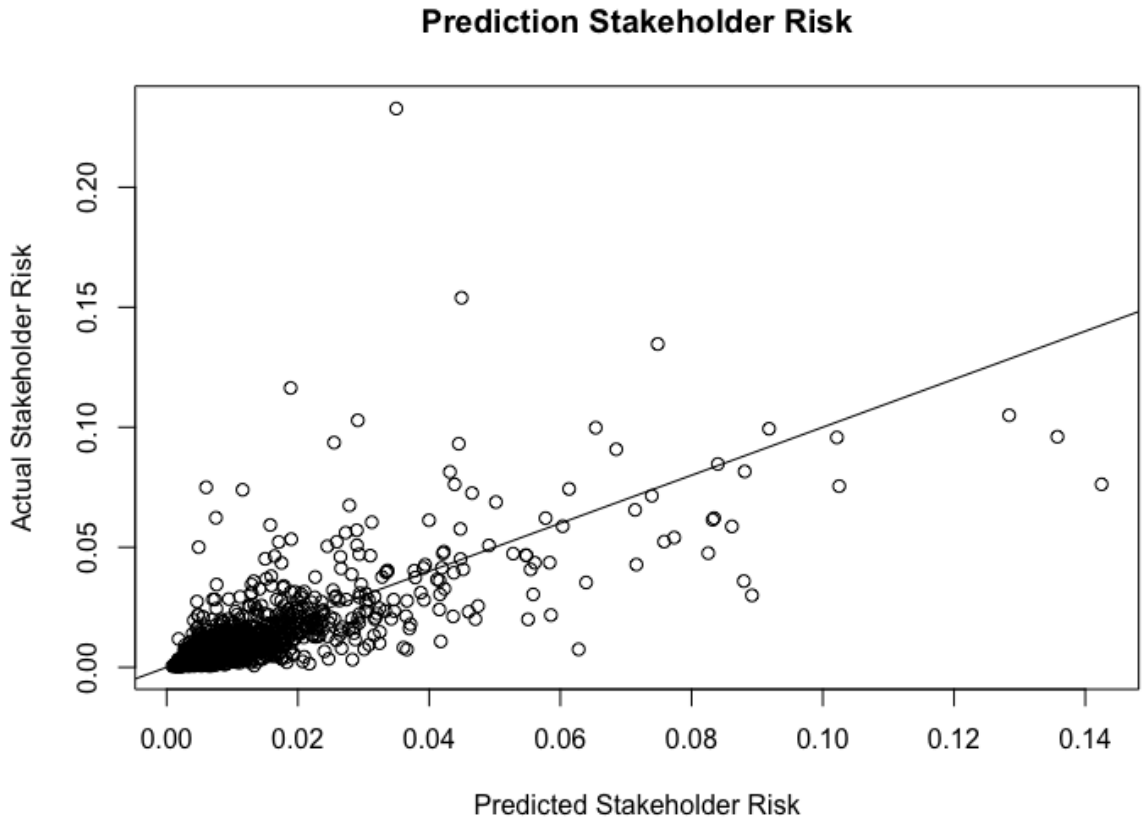


The optimal model, with 500 trees and ten predictors (*mtry*), will be tested on the validation dataset. This model generates an MSE of ± 0.00011, which is lower than the MSE for the training dataset. Besides, the MSE is also slightly lower than the MSE of the linear regression model with time- and firm-fixed effects (0.00011 < 0.00012). The random forest model has an R-squared of 54.88%. This result indicates that the random forest model can explain the variance of the *Stakeholder Risk* better than the linear regression model with time- and firm-

[4] ± Indicates rounded

fixed effects (54.88% > 26.69%). The MSE and the R-squared indicate that the random forest model is better at predicting the *Stakeholder Risk* than the linear regression model with time- and firm-fixed effects. Figure 4 visualizes the prediction performance of the random forest model. The closer the distribution of the dots in Figure 4 is to the vertical black line, the better the model predicts the *Stakeholder Risk.* The dots indicate the predicted values, while the vertical black line corresponds to the actual values.

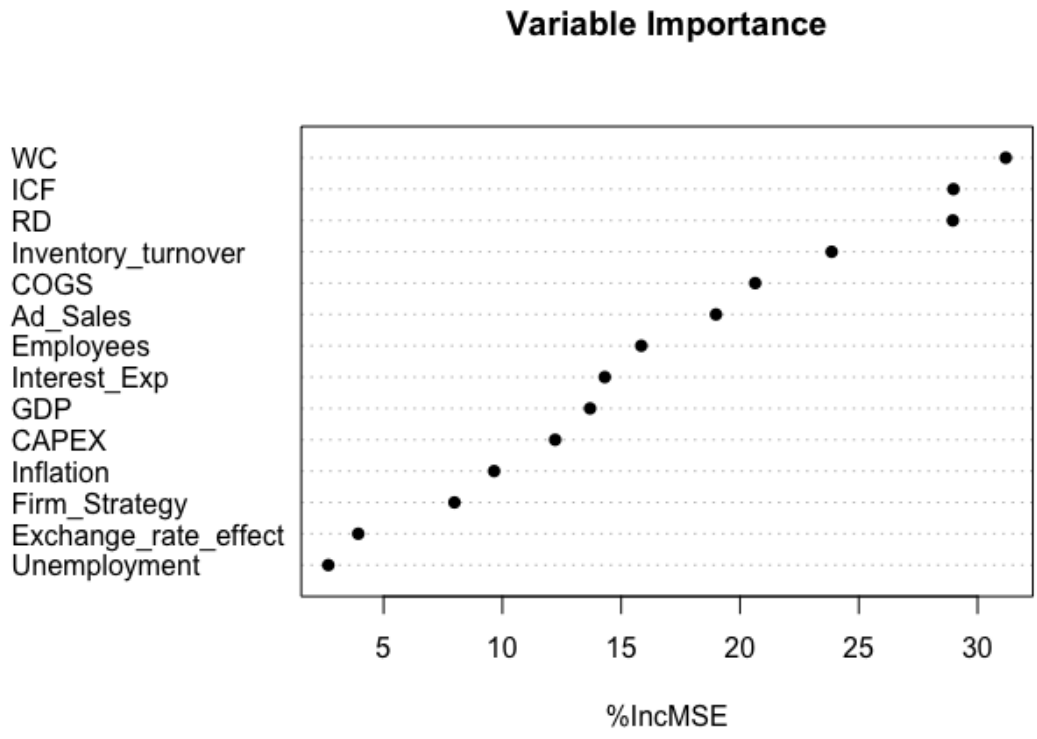
Figure 4. Prediction of the Stakeholder Risk



Most dots are distributed around the left bottom of the graph, indicating a low normalized *Stakeholder Risk*. The predicted values' distribution in the graph's left bottom is close to the vertical black line. However, more to the right of the graph, the dots are distributed more around the vertical black line. The distribution of the predicted values indicates that the optimal random forest model gives somewhat precise predictions of *Stakeholder Risk*; nonetheless, the model outperforms the linear regression model with time- and firm-fixed effects.

The random forest can provide a variable importance plot (Figure 5). This plot shows what will happen to the MSE if one of the variables is excluded. The effect is measured based on the percentual increase in the MSE. Of course, the higher the percentual increase of the MSE, the more crucial the variable is for predicting the *Stakeholder Risk*. The most important variable is the WC (Working Capital) for predicting the *Stakeholder Risk*, with an increase of MSE slightly above 30%. Most variables have a relatively high contribution to the prediction performance of the Stakeholder Risk. Seven of the 14 variables have a percentual increase in MSE of at least 15% when excluded. Besides, out of these seven variables are three marketing variables (R&D, Inventory Turnover, and AD/Sales), three finance variables (WC, ICF, and COGS), and one firm control variable (Employees). The importance of R&D Expenditures is consistent with the regression results since the R&D Expenditures were significant in four of the five regressions. Besides, Inventory Turnover was significant for the EPS risk. However, Ad/Sales was insignificant for all regressions. Nonetheless, it is essential to predict *Stakeholder Risk*. A limitation of this plot is that one cannot conclude the direction or the sign of the predictor variable on the outcome variable.

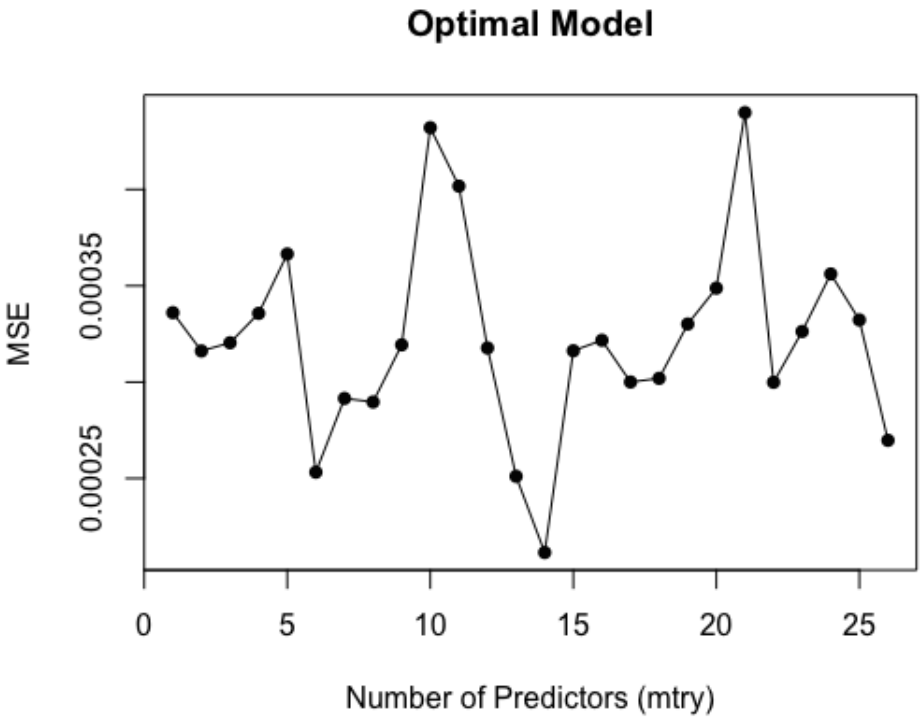
Figure 5. Variable Importance Plot



5.f. Robustness Test of Predicting the Stakeholder Risk with Machine Learning

The regression model with lagged effects performs better than the one without lagged effects. This subsection will measure the prediction performance of a random forest with lagged effects. As before, the best model has the lowest MSE based on the number of predictors (*mtry*). The optimal number of predictors is 14, based on a random forest with 500 trees (Figure 6). The MSE of this model is ± 0.00021 (Figure 6). The MSE of this optimal model with lagged effects is slightly lower than without (± 0.00021 < ±0.00022).

Figure 6. Optimal Model - Lagged effects

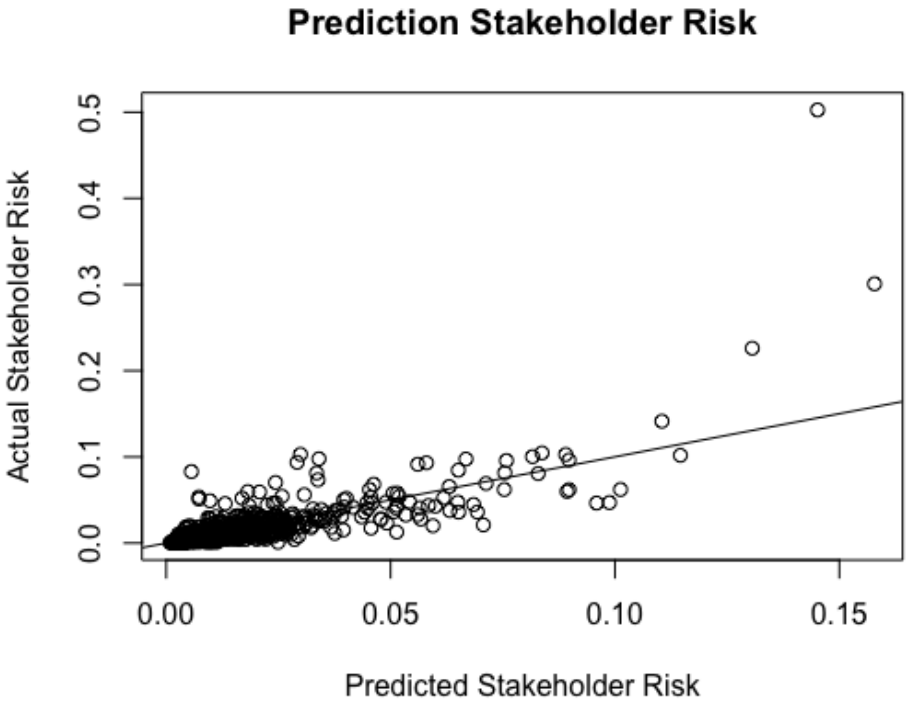


The optimal model, with 500 trees and 14 predictors, is tested on the validation dataset, generating an MSE of ± 0.00019. The MSE of the validation dataset is slightly lower than the MSE of the training dataset (± 0.00019 < ± 0.00021). However, the MSE of the random forest with lagged effects is slightly higher than the random forest without lagged effects (± 0.00019 > ± 0.00011). Lastly, the MSE of the random forest with lagged effects performs slightly worse than the regression model with lagged effects (± 0.00019 > ± 0.00012).

The R-squared generated by this model is 63.31%. The R-squared of the random forest model with lagged effects indicates that this model better explains the variance than the random forest

without lagged effects and the regression model with lagged effects (63.31% > 54.88% ; 30.38%). Figure 7 provides a visual representation of the prediction performance of the optimal random forest model. The distribution of dots around the vertical black line in the figure serves as a clear visual indicator of the model's predictive accuracy. The closer the dots are to the line, the better the model predicts the Stakeholder Risk. The dots represent the predicted values, while the vertical black line corresponds to the actual values.

Figure 7. Prediction of the Stakeholder Risk - Lagged effects

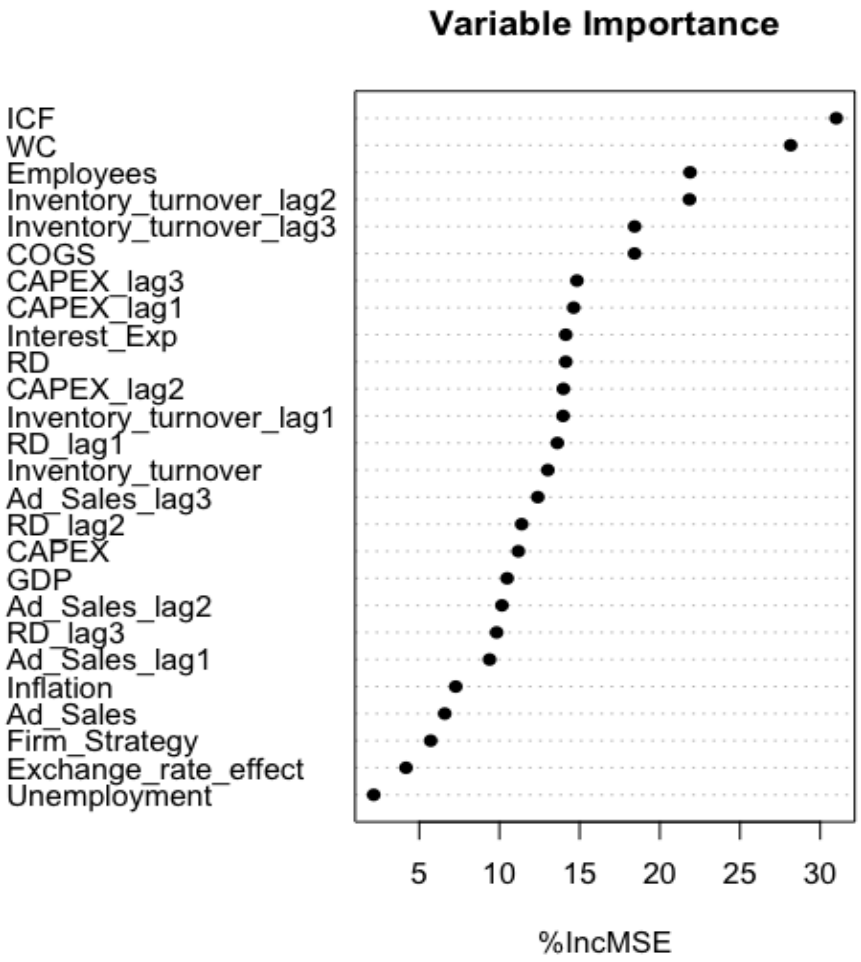


The distribution of the predicted values is closely around the actual values (Figure 7), similar to Figure 4. However, as mentioned before, this model's MSE is worse than that of the random forest model without fixed effects. In other words, the random forest model without lagged effects predicts more accurately than the random forest model with lagged effects. Nonetheless, the model can predict quite accurately, except on the right-hand side of the graph.

The variable importance plot (Figure 8) reveals that excluding certain variables can significantly impact the MSE. The most important variables for predicting *Stakeholder Risk* are ICF and WC. Inventory Turnover with a lag of 2 & 3 years and CAPEX with a lag of 1 & 3 years are the most important marketing variables. Notably, the introduction of lagged effects

has reduced the importance of R&D in predicting *Stakeholder Risk*, which is an interesting finding.

Figure 8. Variable Importance Plot - Lagged Effects



5.g. The Hypothesis Conformation Overview

In this subsection, a hypothesis confirmation table is provided (Table 14). The eleven hypotheses are considered in this table.

Table 14. The Hypothesis Confirmation Table

	Hypothesis	Confirmation
	Customer Risk	
(1)	CAPEX has a negative effect on the Customer Risk.	NC
(2)	R&D Expenditures has a negative effect on the Customer Risk.	NC
(3)	Inventory turnover has a negative positive effect on the Customer Risk.	NC
(4)	Ad/Sales has a negative effect on the Customer Risk.	NC
(5)	Differentation Strategy has a negative effect on the Customer Risk.	NC
	Shareholder Risk	
(6)	CAPEX has a negative effect on the Shareholder Risk.	NC
(7)	R&D Expenditures has a negative effect on the Shareholder Risk.	NC
(8)	Inventory turnover has a negative effect on the Shareholder Risk.	NC
(9)	Ad/Sales has a negative effect on the Shareholder Risk.	NC
(10)	Differentation Strategy has a negative effect on the Shareholder Risk.	NC
	Stakeholder Risk	
(11)	The random forest provides more accurate predictions of the Stakeholder Risk than the linear regression.	C

Confirmed (C) indicates that evidence supports the hypothesis. Not Confirmed (NC) indicates that there needs to be more evidence to support the hypothesis.

As mentioned in Table 14, evidence lacks to support the hypothesis about the effectiveness of marketing predictor variables in lowering *Customer*- and *Shareholder Risk*. In other words, the *Stakeholder Risk*. Some marketing predictor variables provided significant results; however, the signs of the results showed the opposite of the hypotheses (e.g., CAPEX, R&D Expenditures, and Inventory Turnover). The Cost-Leadership Strategy has a significantly lower effect on the OCF Risk than the Differentiation Strategy, which contradicts hypothesis 10. Nonetheless, CAPEX and R&D Expenditures tend to have a significant negative effect on the *Stakeholder Risk* with a lag of three years, confirming the lagged effects of previous research (Keller, 1993; Rechheld, 1996; Lukas et al., 2003; Currim et al., 2012; Schulze et al., 2012;

Lee et al., 2015). The drivers (e.g., *Customer*- or *Shareholder Risk*) of this significant lagged effect on the *Stakeholder Risk* since the lagged effects focused exclusively on the *Stakeholder Risk*. This paper found evidence about the random forest, which was better at predicting the *Stakeholder Risk* than the linear regression with time- and firm-fixed effects. The random forest was able to explain more variance of the *Stakeholder Risk* and generated a lower MSE than the linear regression model with time- and firm-fixed effects. However, the prediction power reduced slightly after the introduction of lagged effects.

6. Discussion

The results of this paper indicate that some marketing variables (e.g., CAPEX, R&D Expenditures, Inventory Turnover, and Firm Strategy) had a significant effect on some of the risks. However, aside from the Cost-Leadership Strategy, these effects have contributed positively to the risks. The robustness test showed that CAPEX and R&D significantly negatively impact the *Stakeholder Risk* for a three-year lag. The lagged effect aligns with previous research results (Keller, 1993; Rechheld, 1996; Lukas et al., 2003; Currim et al., 2012; Schulze et al., 2012; Lee et al., 2015). Currim et al. (2012) explained that marketing expenditures impact profits negatively in the short term while contributing positively in the long term. The results provide relevant insights for management. Management should know that CAPEX and R&D have a long-term effect, which pays out three years after the investment. The costs of these investments increase the risk in the first two years of the investment; however, they lower the risk three years after the investment. This long-term effect makes sense since CAPEX and R&D have a long-term focus. CAPEX can be an investment into a new facility or customer platform, which creates *high* costs at the beginning and pays out the years after this investment. Same for R&D, developing a new product is time, and money-consuming but pays out when the product is on the market. When making decisions, management should be aware of time-lagged effects because investments that initially seem to perform poorly can be attractive in the long term. Neglecting these investments can cost a company in the form of a higher *Stakeholder Risk*. Also, the strategy of the firm matters to a certain extent. The firms' strategies differed significantly for the OCF Risk, indicating that the choice of strategy matters for this risk. Cost-Leadership Strategy lowers the OCF Risk significantly compared to the Differentiation Strategy. The other marketing variables (e.g., Inventory Turnover and Ad/Sales) did not impact the risks significantly. Some lagged effects of these variables had a negative effect on the Stakeholder Risk; nonetheless, this effect was insignificant. This paper assumes Inventory Turnover as an indicator of customer loyalty. This indication is partly valid since the Inventory Turnover can indicate how often consumers buy the products/services; nevertheless, Inventory Turnover can also be affected by inventory management. Keeping inventories low may create higher turnover. The turnover does not necessarily have to indicate more customer loyalty. Lastly, Ad/Sales may have contributed little to the risks since most advertisements can focus on the short term. Hanssens (2015) explained that most marketing analyses focus on the short-term impact. Besides, managers are evaluated based on the quarterly failure and success of the campaigns, resulting in spending closer to the purchase

point (Hanssens, 2015). This myopic mindset may explain why Ad/Sales is not significant for both yearly as it is a lagged contribution to risk.

The second goal of the paper was to research if machine learning methods could improve the prediction of Stakeholder Risk. The random forest performs better than the linear regression model with time- and firm-fixed effects since it has a slightly lower MSE. Besides, the random forest can explain more variance than the linear regression model with time- and firm-fixed effects. In other words, the random forest model can improve the prediction performance of the *Stakeholder Risk*. However, one should know that the random forest operates as a black box model. The model provides accurate prediction besides visualizing which variables, if excluded, drive the MSE; nonetheless, the impact of each variable on the *Stakeholder Risk* needs to be interpretable. This interpretability issue is also known as the accuracy versus interpretability consideration, an issue that is not only prevalent in finance or marketing but also in healthcare (Luo et al., 2019). For interpretation, the linear regression model with time- and firm-fixed effects is easier to understand; however, the accuracy could be worse for this model.

Of course, some limitations may have influenced the results of this paper. First, the analysis did not include a sector split. The effectiveness of the marketing effect may differ per sector, indicating that the results may vary from the aggregated model used in this paper. Second, in this paper, it was only on the S&P 500. This index focuses on the US market and large-capitalization companies (Smith, 2023; Kenton, 2024). The effectiveness of marketing may differ per country. The marketing effectiveness results could vary for Europe or Asia compared to the US. Additionally, the firm's size may impact the marketing effect. Third, this analysis used quarterly data, translated into yearly data, to measure the risk of the outcome variables. The transition into yearly data may have led to two issues: (1) The analysis did not consider seasonality; however, the seasonality is assumed to partly average out because of the time range of 23 years. (2) It cannot capture short-term effects, for example, the risks in revenue shortly after an advertisement or when the costs occur in the corresponding year. Fourth, as mentioned before, in this paper, Inventory Turnover was understood as an indication of sales, but of course, it is also affected by inventory- management or control. Less goods in the inventory does not necessarily indicate better sales. In other words, Inventory Turnover may not be an optimal marketing indicator. Next, the *Stakeholder Risk* was measured based on the *Customer-* and *Shareholder Risk*. Of course, *Stakeholder Risk* is affected by multiple risks (e.g., supplier-

, environmental- and social risk); however, this is not considered since the focus was on the marketing-finance interface. Inclusion of all the other risks in the *Stakeholder Risk* would likely provide different results. Nonetheless, this is interesting for future research.

Lastly, other prospects for future research are (1) The exploitation of the short-term versus long-term effects of marketing investments on the risk. What is the sustained impact of marketing investments over time? Machine learning methods can help to explore this question. (2) A sector-specific analysis. Sectors may behave very differently in marketing activities. A sector-specific analysis would contribute to finding out which marketing metrics contribute negatively or positively to the risk per sector.

7. Conclusion

The goal of this paper was to find a way to review the accountability of marketing based on their contribution to the *Customer-*, *Shareholder-*, and *Stakeholder Risk*. Creating accountability would improve the budget position of the marketing departments in the organization and improve the mutual understanding with the finance department. Emerging the research question: "*To what extent do marketing metrics influence Stakeholder Risk? Additionally, how can machine learning methods be employed to analyze and predict the impact of these marketing metrics on Stakeholder Risk in the US?"*. The hypotheses emerging from the first part of the research question were to analyze the contribution of marketing, divided into a focus on the *Customer*, *Shareholder-*, and *Stakeholder Risk*. The hypotheses assumed that the marketing variable would lower the risk, indicating a significant negative effect on the risk. Unfortunately, there was not enough evidence to support these hypotheses. The marketing variables do not significantly impact the outcome variable or tend to have a (significant) positive effect on the outcome variable, indicating an increase in the risk. However, interestingly, the firm's strategies seem to matter for the OCF Risk; a Cost-Leadership Strategy is associated with a lower expected OCF Risk than a Differentiation Strategy.

However, the three-year lagged effects of CAPEX and R&D significantly lower the expected *Stakeholder Risk.* This suggests that these investments may have a stable payout after three years, thereby reducing *Stakeholder Risk*. Marketing and finance management should focus on the long-term effectiveness of marketing investments. They can use *Stakeholder Risk* as an outcome variable to measure the effectiveness of their investments.

The final hypothesis emerging from the second part of the research question was to investigate whether machine learning methods can enhance the prediction of *Stakeholder Risk*. The results show that the random forest model significantly improves the prediction performance of the *Stakeholder Risk*. This suggests that management should consider using such models to forecast the effect of a specific investment, as they can provide accurate predictions of the impact on the *Stakeholder Risk*. However, for a clear interpretation of the impact and magnitude of the investment on *Stakeholder Risk*, the linear model with time- and firm-fixed effects remains a more straightforward and interpretable approach.

In conclusion, based on the results, the research question: "*To what extent do marketing metrics influence Stakeholder Risk? Additionally, how can machine learning methods be employed to analyze and predict the impact of these marketing metrics on Stakeholder Risk in the US?"*. The results of this paper provide evidence that marketing variables (CAPEX and R&D) increase the *Stakeholder Risk*. Besides, other marketing variables (such as Inventory Turnover, Ad/Sales, and Firm Strategy) had an insignificant impact on the risks. In other words, evidence lacks support that marketing metrics lower the Stakeholder Risk in the same year as the cost occurred.

Despite that, some three-year lagged marketing variables (CAPEX and R&D) lower the expected *Stakeholder Risk*. In other words, investments in CAPEX and R&D have a long-term effect. Lastly, the random forest improves the prediction performance of the *Stakeholder Risk*. The random forest model without lagged effects should be used to create accurate predictions of the *Stakeholder Risk* since this model performs slightly better than the model with lagged effects. However, it is better to analyze the magnitude and sign of the effects of marketing metrics through the time- and firm-fixed effects model since this model is more straightforward to interpret.

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