MASTER THESIS

MARKET VALUE OF AI: DOES INVESTING IN AI PAY OFF?

MSC BUSINESS ADMINISTRATION

FINANCIAL MANAGEMENT

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PREFACE

Dear reader,

This research marks the conclusion of my Master's degree in Business Administration at the University of Twente. Throughout this program, I specialised in the field of Financial Management. This thesis represents the final step of my studies, integrating the knowledge and skills I have acquired over the past years.

Conducting this research has been an enriching experience, offering me the opportunity to delve into the complex and evolving relationship between R&D investments, media attention, and AI-related announcements and their impact on market value. This journey has not only enhanced my understanding of financial management but also equipped me with critical analytical and research skills.

I would like to express my sincere gratitude to my first supervisor, Jeroen Sempel, whose guidance and support has been invaluable throughout this process. His insights and feedback have significantly shaped the direction and quality of this work. I am also grateful to my second supervisor, Bert Bruggink, for his feedback and guidance during this academic journey.

Furthermore, I would like to extend my thanks to my family, girlfriend, and friends for their unwavering support during my studies and throughout all my experiences during this period. Their belief in my abilities has been a constant source of motivation.

I hope this thesis provides valuable insights into the financial implications of innovation and specifically the value of artificial intelligence, and I look forward to applying the lessons learned in my future professional endeavours.

Sincerely,

Coen van Orlé

ABSTRACT

This study investigates the effect of investments in artificial intelligence on the market value of publicly traded companies, focusing on three primary hypotheses. Following a structured approach, which starts broad and becomes more specific, this research examines the relationship between R&D investments and market value, the influence of media attention on market value, and the market's reaction to AI-related announcements.

Data was collected from firms listed on the S&P 500 index over the period from 2013 to 2023. The methodology includes three main steps. First, regression analysis using both the Ordinary Least Squares and Fixed-Effects methods to evaluate the immediate and delayed effects of R&D investments on market capitalisation. Second, similar regression methods were conducted to assess the impact of media attention, measured as the number of AI-related news announcements, on market value. Third, an event study was conducted to investigate the market reaction following AI-related news announcements. Using a funnel approach, the sample starts with 500 firms for the R&D investment analysis, narrows down to 50 firms for the media attention analysis, and further focuses on 5 firms for the event study.

The results demonstrate a significant positive impact of R&D investments on market value in the short-term, with diminishing effects over the long-term. Media attention significantly influences market value, indicating that firms with higher visibility of their AI initiatives benefit from increased investor confidence. Event studies reveal that AI announcements lead to varied market reactions, with the overall sample showing positive abnormal returns as an immediate effect.

This research underscores the critical role of continuous innovation and strategic communication in enhancing market value. The findings provide valuable insights for managers and investors regarding AI investments, highlighting both the benefits and potential risks associated with these investments.

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1. INTRODUCTION

In the dynamic landscape of modern business, organisations continuously seek innovative strategies to enhance their competitiveness and drive growth. Companies are increasingly focusing on leveraging technological advancements to create value, improve efficiency, and gain a competitive edge. Historically, the emergence of Information Technology (IT) brought a significant transformation to business operations. This forced companies to integrate new systems and processes to stay competitive. This period of IT adoption showcased the impact technological advancements could have on firm performance and market value. Similarly, following the IT revolution, artificial intelligence (AI) has now emerged as a significant driver of innovation in the business world.

Though AI has seen a boost recently, it is not a novel technology. Instead, AI has been around for a while and has helped advance computing for more than 60 years. It has supported the creation of new breakthroughs and has been used in a variety of contexts, leading to a constant stream of innovations (Berente et al., 2021). AI technologies have been integrated into various business operations to improve efficiency, enhance customer interactions, and improve data-driven decision-making. The last decade has witnessed a transformative technological shift marked by substantial developments in AI technologies and their widespread commercial application (Furman & Seamans, 2019). For instance, in the banking industry, Bank of America's virtual assistant called Erica, and the Bank of New York Mellon Corp's implementation of over 220 "bots" exemplify the integration of AI to enhance customer interactions and automate repetitive tasks (Castellanos, 2018). International giants like Amazon, Apple, and Facebook leverage AI to successfully automate their operations, and even Domino's Pizza employs AI to optimise delivery times (Marr, 2019; Minevich, 2020). These examples illustrate the impact of AI across different sectors, which introduces a new layer of complexity and opportunity in business operations.

Many enterprises believe that AI implementation fosters competitive edges and foresee that AI implementation will lead to new business opportunities (Haan, 2023). For example, AI-driven predictive analysis can help companies anticipate market trends and customer preferences, enabling more strategic decision-making and competitive positioning (Agrawal et al., 2019). Moreover, it can improve customer experiences by personalising interactions and providing real-time support, which can enhance customer satisfaction and loyalty (Kaplan & Haenlein, 2019). Also, AI's ability to process vast amounts of data and generate actionable insights can lead to the development of new business models and revenue streams, thereby creating competitive advantages. For instance, the study by Agrawal et al. (2019) indicates that investors perceive AI investments as a sign of a firm's forward-thinking strategy and potential for future growth, thus positively impacting stock prices.

However, among the optimism surrounding AI's potential, questions arise regarding its tangible impact on financial performance. Due to the scope and speed of AI technology deployment, concerns about potential ethical dilemmas are raised among many stakeholders, especially in high-stakes decision situations (Coeckelbergh, 2020). Also, research by Brynjolfsson and McAfee (2014) suggests that investors may exercise caution due to the uncertainties and risks associated with AI implementation, such as the high costs, potential job displacement, and the unpredictable nature of AI outcomes. There are also concerns about the return on investment (ROI) of AI projects, as the benefits may not be immediately apparent and can take years to materialise (Huang & Rust, 2018). Moreover, the integration of AI into existing systems often requires significant changes in organisational processes and culture, which can be met with resistance from employees and management (Lichtenthaler, 2019).

Existing studies related to IT investments reveal a positive correlation between IT investments and the market value of firms (Dehning et al., 2003; Subramani & Walden, 2001). These studies suggest that technological advancements, when effectively implemented, can lead to increased firm valuation and investor confidence. Nevertheless, the reception to AI adoption by investors remains a variable, with some viewing it as a positive development while others exercise caution. Given these mixed perceptions, the crucial question remains: Can AI technologies bring benefits and value to companies?

Despite the optimistic outlook, there exists a scarcity of studies providing concrete proof of AI's impact on businesses (Huang & Lee, 2023). Managers face the challenge of presenting this evidence to stakeholders and shareholders, convincing them that investing in AI holds the promise of generating new revenue for their businesses. Also, while AI has the potential to revolutionise business operations, the high costs associated with its implementation and maintenance can be prohibitive, especially for smaller firms. As this study examines the impact of AI investments on the market value of publicly traded companies, it aims to address the relevant question: Does investing in AI pay off for listed companies? Through explorative analysis, to gain insights and increase understanding of this particular topic, this study answers the following research question:

How does the adoption of AI technologies impact the market value of publicly traded companies?

Existing literature underscores the difficulty of measuring how much companies invest in AI. This challenge arises because firms often do not disclose the exact amounts they allocate to AI projects and investments, making it hard to quantify the investments and evaluate their impact directly (Makki & Abdallah, 2019). Additionally, AI investments are often embedded within broader R&D expenditures, further complicating the measurement. The lack of standardised reporting on AI spending means that traditional financial analysis methods fall short in capturing the full picture of AI investment.

To address these challenges, this study adopts a structured methodology similar to a funnel, which narrows the focus from general R&D investments to media attention and finally to news announcements. This approach allows for a comprehensive analysis that starts broad and becomes more specific, providing a detailed understanding of AI investments' impact on market value. The funnel methodology is chosen for its ability to systematically narrow down the scope of analysis, ensuring that each step builds on the previous one. Starting from broad R&D investments, moving to media attention on AI, and ending with market reactions to specific AI announcements, this method progressively refines the research focus. This structured approach ensures a thorough examination of the topic, addressing the complexities and nuances of AI investments.

The first part of the study examines investment in innovation, because AI investments are part of innovation. Specifically in R&D, to understand its correlation with firm market value. R&D investments are crucial for innovation and long-term growth, but their impact on market value can vary significantly depending on various factors such as industry, firm size, and market conditions. By analysing general R&D expenditures, this study aims to determine whether these investments lead to increased market capitalisation and how investors perceive the value of R&D activities. This step is relevant because it provides a foundational understanding of how innovation investments affect market value, setting the stage for a more focused analysis of AI investments.

The second part of the study focuses on the effect of media attention on the market value of firms. Media coverage can significantly influence investor perceptions and confidence, consistent with the signaling theory (Connelly et al., 2011). Positive media attention can enhance a firm's reputation and attract investor interest, while negative coverage can have the opposite effect. By analysing media attention related to AI, the study aims to understand how public perception of AI initiatives affects investor behaviour and market valuation. This step is crucial as it highlights the role of external information in shaping market reactions to AI investments. Media attention serves as an intermediary between the broad R&D investments and specific AI announcements, showing how the market's interpretation of AI investments can be influenced by external sources.

The third part of the study delves into the market reactions to AI-related announcements. Using the event study methodology, which captures the immediate effect of specific events on stock prices, the study analyses 110 AI-related announcements from five listed companies. This approach provides insights into how investors respond to AI initiatives in real-time, reflecting their expectations about the potential (future) benefits and risks associated with these investments. This step is particularly relevant because it isolates the impact of AI announcements, offering a clear view of investor sentiment and market dynamics in response to AI investments. It provides detailed evidence on investor's immediate reaction to AI initiatives, including their perspectives on the long-term benefits of these investments.

By combining these three parts, the study provides a holistic view of AI investments' impact on market value, addressing the complexities and nuances involved. This structured approach ensures a thorough examination of the topic, offering valuable insights for investors, managers, and policymakers interested in understanding the value of investing in AI.

The study is structured as follows. First, the literature review covers the topics of business valuation, value creation, AI, the dual perspective of AI investments, media attention, and market reactions to AI announcements. Using this knowledge, three hypotheses are formulated that underpin the research methodology. Employing the structured approach of the three steps, akin to a funnel, the three hypotheses are tested using the approach described in the research methodology. After describing the data used, the results are presented and interpreted. Finally, the results are discussed in the discussion chapter and a conclusion is drawn, followed by limitations and recommendations for future research.

2. LITERATURE REVIEW

This chapter navigates through key themes crucial to the investigation of AI and its impact on market value. It starts by clarifying business valuation methods and explaining why companies want and should create value. After diving into the topic of innovation, R&D, and lagged effects of investments in R&D, the topic of AI is covered. An overview of AI is given, exploring its evolution and fundamental components. After this, the intrinsic value of AI and innovation and several negative aspects of AI are examined, acknowledging its potential benefits and costs. Further, two methods of measuring AI investment are discussed: media attention and the reaction of the market to AI announcements. Finally, the hypotheses are formulated to guide this research inquiry. The literature review synthesises current research, identifies gaps, and sets the stage for the research methodology.

2.1 BUSINESS VALUATION

Business valuation is the process of determining the economic value of a business or company. According to Koller et al. (2020), business valuation is fundamentally about determining the economic value of a company. This involves a comprehensive assessment of the company's ability to generate future cash flows and the associated risks. The primary goal is to provide a clear, objective estimate of what a company is worth, which is crucial for making informed business decisions related to mergers, acquisitions, and strategic planning. Companies want to know how much the firm's worth, and how value can be created.

A valuation procedure involves determining the theoretically appropriate value of an investment, company, or asset instead of its cost or current market value. Consulting firms frequently perform valuations in mergers and acquisitions, strategic planning, capital financing, and securities investment purposes. In the case of mergers and acquisitions, advisors use valuation to provide acquiring firms with an indication of the highest price they should pay for a target company and selling firms with an indication of the lowest price at which they should sell their company. Next to that, it is valuable for a firm to know its own firm value, to help identify what projects a company should invest.

According to Schmidt (2023), there are four main reasons for performing a valuation. Firstly, to buy or sell a business. The worth of a firm will typically differ between buyers and sellers. A valuation would be helpful for both parties when deciding whether to buy or sell, and at what price. Secondly, for strategic planning. Only investments in initiatives that raise a company's net present value should be made. As a result, investments are chosen based on the possibility of future wealth generation and profitability. Thirdly, there is capital financing. During financial negotiations with banks or potential investors, demonstrating the company's worth and its ability to generate cash flow enhances its credibility with both equity investors and lenders. Lastly, there is securities investing. Purchasing a security, such as a stock or a bond, is simply a wager that the security's market value isn't being accurately reflected. Determining that intrinsic value requires a valuation (Schmidt, 2023).

In short, valuation is crucial for various reasons. Accurate business valuation helps investors and stakeholders understand the worth of a company, facilitating informed decision-making. It ensures that all parties have a clear understanding of the company's value, which is essential during negotiations. Additionally, business valuation is important for financial reporting and compliance, ensuring that the financial statements accurately reflect the company's worth (Damodaran, 2006).

2.1.1 Methods

There are various methods to value companies, which can be classified in six groups: balance sheet, income statement, mixed (goodwill), cash flow discounting, value creation, and options (Fernández, 2007). Fernández dives deeper into the first four groups, which are the main groups comprising the mostly used company valuation methods.

The balance sheet method uses book values. It estimates the value of its assets by considering that a company's value lies in its balance sheet. These methods include book value, adjusted book value, liquidation value, and substantial value. Book value refers to the value of shareholders' equity stated in the balance sheet. Adjusted book value seeks to overcome the shortcomings of pure accounting criteria by aligning asset and liability values with their market values. Liquidation value calculates the company's worth if it were to be liquidated, subtracting liquidation expenses from adjusted net worth. Substantial value represents the investment required to form an identical company, taking into account only the assets used in operations (Fernández, 2007).

For the income statement method, it is based on the company's income statement. It seeks to determine the value by its sales, earnings, or other indicators. This includes the Price Earnings Ratio (PER) method, which values equity by multiplying net income by a ratio. Another approach is valuing companies using multiples like sales, EBIT, or EBITDA (Earnings Before Interest, Taxes, Depreciation, and Amortisation). For instance, insurance companies might be valued by multiplying their annual premiums by a specific multiple (Fernández, 2007).

Mixed methods, or goodwill-based methods, are based on the intangible assets of a company. Goodwill represents the value of intangible assets that do not appear on the balance sheet but give the company an advantage. These methods combine a static valuation of the company's net assets with a capital gain related to future earnings. Approaches under this category include the classic method, which adds net substantial value to a multiple of net income, and the Union of European Accounting Experts (UEC) method, which calculates goodwill based on profits (Fernández, 2007).

By projecting future cash flows and discounting them at a rate matched with the risk of those flows, the fourth method, known as cash flow discounting, aims to ascertain the company's value. Cash flow discounting methods, considered conceptually correct, involve forecasting future cash flows and discounting them using the Weighted Average Cost of Capital (WACC). This method includes calculating the value using free cash flow, equity cash flow, or capital cash flow. The company's value is often calculated as the sum of its debt and equity, discounted at rates reflecting their respective risks (Fernández, 2007).

These methods provide a structured approach to company valuation, each with specific applications and considerations based on the nature and circumstances of the company being evaluated.

2.1.2 Financial markets

Over the years, there have been significant shifts in market behaviour (Baier-Fuentes et al., 2019). These shifts have impacted financial investments during periods of robust growth and recessions, driven by cycles of expansion and crisis. These cycles include hyperinflation, deflation, and bubbles in sectors like real estate, energy, technology, finance, and credit, which have challenged existing theories of value creation. Other causes include market volatility in the face of structural changes such as monetary unions, technological changes, monetary expansions, and the opening of isolated economies. In addition, there has been a reduction in the relevance of historical variables that determine the value of companies, such as growth, income, and inflation (Trkman & Trkman, 2018).

According to the Efficient Market Hypothesis (EMH), which asserts that asset prices fully reflect all available information, companies must continually innovate to generate new information and create a competitive edge (Fama, 1970). The ability to add value not only attracts investors but also ensures long-term viability in a competitive environment. For instance, IT investments enable the acquisition and utilisation of advanced technologies, thereby amplifying the potential for groundbreaking discoveries and developments. Also, the allocation of resources towards skilled personnel ensures that the company has the necessary expertise to navigate the complexities of emerging technologies (Cohen & Levinthal, 1990).

The valuation of businesses in this dynamic market is a process influenced by various factors, including market reactions, unexpected events, and communication signals. Next to the EMH (Fama, 1970), the signaling theory states that companies can get valuable information to the market through signals such as announcements or media coverage, which in turn can influence investor perceptions and behaviour (Connelly et al., 2011). The valuation landscape is characterised by the market's rapid response to signals and unforeseen events shared through public media. The reactions of investors are tied to the sentiment of these announcements, leading to fluctuations in stock prices and the emergence of abnormal returns.

2.2 VALUE CREATION

Since the financial crisis of 1929, the business and financial sectors have been assessing what factors contribute to long-term value in terms of trends, bubbles, or irrational excitement. The pursuit of understanding value creation in companies has become a widely explored topic, especially in the selection of stocks in public markets. Over the past 80 years, various studies and theories have created frameworks to understand value creation, influenced by the different ideas of each era and the ups and downs of the economy (Lafont et al., 2020).

The pursuit of value creation stands as a fundamental objective for companies aiming to thrive and excel in the market. Value creation serves as a cornerstone for businesses seeking sustained growth and profitability. The faster companies can increase their revenues and deploy more capital at attractive rates of return, the more value they can create. In fact, businesses add value when their returns on capital rise or when they grow at a rate higher than their cost of capital. Regardless of whether they boost earnings or otherwise provide their financial statements a more impressive appearance, actions that do not result in an increase in cash flows over time will not add value (Koller et al., 2020). Schumpeter (1934) underscores the importance of continual innovation for companies to generate new information and establish a competitive edge. Schumpeter's concept of "creative destruction" emphasises the role of innovation in disrupting existing markets and fostering economic development. In the context of business value creation, innovation is not merely a strategic option but a necessity for survival and prosperity.

Innovation decisions are the most fundamental strategic decisions for every firm, since innovation today is the vital instrument of firms to enter new markets, to increase current market shares, and to strengthen the competitive edge. As a term, innovation is not only related to products and processes, but is also related to marketing and organisation. Actually, the key reason for innovativeness is the desire of firms to obtain a better competitive edge and increased business performance (Günday *et* al, 2011). Schumpeter (1934) describes different types of innovation: new products, new methods of production, new sources of supply, the exploitation of new markets, and new ways to organise a business. According to Drucker (1985), innovation is defined as the process of equipping in new, improved capabilities or increased utility.

2.2.1 Innovation strategies

Companies employ various strategies to innovate. The “OECD Oslo Manual” is widely regarded as the essential reference source for describing, identifying, and categorising innovations at the firm level. It serves as the main international foundation for guidelines for defining and evaluating innovation activities as well as for the collection and use of related data (Günday et al., 2011).

In the manual, four different innovation types are introduced. Firstly, there is product innovation. A product innovation is the launch of a quality service that is novel or markedly enhanced in terms of its features or intended applications. Examples of notable enhancements include added software, user-friendliness, technical specifications, components and materials, and other functional aspects. So, the term product covers both goods and services. Secondly, there is process innovation. A process innovation is the application of a brand-new or enhanced delivery or production method. This involves making considerable adjustments to techniques, tools, and/or software. Process innovation can be implemented to lower manufacturing or delivery costs per unit, improve quality, or create or supply new or substantially improved products. Thirdly, there is marketing innovation. A marketing innovation is the adoption of a new marketing strategy that involves considerable adjustments to the product’s placement, promotion, design, or price. Marketing innovations target improved customer service, expanding into untapped markets, or repositioning a company's product to increase sales. Finally, there is organisational innovation. The use of a new organisational strategy in the company's business operations, workplace layout, or external interactions constitutes the last type of innovation. Organisational innovations often lead to higher firm performance through lower transaction and administrative costs, increased worker productivity and workplace satisfaction, access to non-tradable assets, or lower supply costs. Training programs for employee development and retention, or the start of a supplier development program, could be examples of organisational innovation (OECD, 2005).

Organisational accomplishments as a consequence of renewal and improvement initiatives that take into account several facets of the firm's innovativeness is known as innovative performance (Günday et al., 2011). To secure innovation and economic growth, investment in R&D has been regarded as one of the key strategies (Trajtenberg 1990).

2.2.2 R&D Activities

Innovation is often manifested through strategic investments of profits in R&D (Trajtenberg 1990). These investments serve as proactive measures to enhance their capabilities, stay abreast of market dynamics, and ultimately create value. Innovation, in this context, extends beyond product development and includes investments in technology, R&D, employee training, and process optimisation. Technology is a pivotal area of investment for companies aiming to innovate. Allocating resources to acquire and develop cutting-edge technologies enables businesses to enhance efficiency, streamline operations, and deliver innovative products or services. R&D initiatives further solidify a company's commitment to innovation by allocating resources to explore new ideas, technologies, and solutions (Cohen & Levinthal, 1990). R&D investments contribute not only to immediate product innovation but also to the long-term competitiveness and adaptability of the company. Within R&D expenditures, companies allocate resources to various critical components such as IT, human capital (employees), and streamlined processes. These multifaceted investments aim to enhance the innovation landscape within the organisation.

R&D Allocation

Investing in R&D is not an automatic guarantee of increased firm value; it requires strategic planning to ensure that it fosters a competitive advantage. R&D spans a broad spectrum of activities crucial to the innovation process. Typically, research involves the initial pursuit of scientific or technical breakthroughs, while development focuses on transforming these discoveries into tangible product or process improvements. This domain can be further divided into basic research, applied research, and development activities. Basic research explores fundamental aspects across physical and biological sciences, and applied research tackles specific projects that can vary widely across different industrial product groups (Link, 1982). This is illustrated in Figure 1.

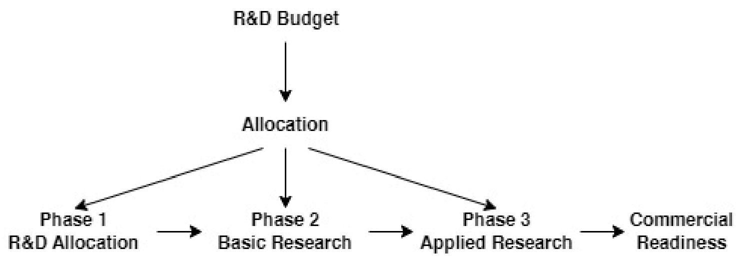


Figure 1. Traditional simplified view of R&D allocation (Hansen et al., 1999)

At a deeper level, the connection between an industry's R&D spending and a firm's R&D spending is explained by the “spillover” effect. This happens when companies learn from and build on each other's innovations. To benefit from this, firms need to develop the ability to use knowledge from others, such as by hiring scientists to study what other companies are doing (Lev & Sougiannis, 1996). In fact, researchers in economics have found that companies with more R&D spending are more adept at utilising information produced outside of their own organisation than are companies with lower R&D spending (Evenson & Kislev, 1973).

Costs and benefits of R&D

Much work has gone into examining how, given the conflicting results of earlier research, the costs and benefits of R&D activities may be balanced. Examining how the effects of R&D activities differ across industries is one of the breakthroughs. For instance, while announcements of increased R&D spending often result in significantly favourable share prices, Chan et al. (1990) find inconsistent results for enterprises with high and low technology. Increases in R&D spending announced by high-tech companies are linked to positive abnormal returns, while announcements made by low-tech companies are linked to negative abnormal returns. Furthermore, Eberhart et al. (2004) discovered that high-tech companies perform unusually well compared to low-tech companies following increases in R&D investment. This body of work suggests that there may not be a universally applicable concept for the best way to spend money on R&D. This dispute may arise from a failure to consider the interacting process between R&D effort and the firm’s internal and external environment (Guo et al., 2018).

The literature has mixed results regarding the market value effect of R&D expenditures. Sougiannis (1994) showed that the stock market values R&D expenditures with a more than proportional effect, but after such investments mature, with a lag.

Using older data from 1987 to 1998, which includes different industry profiles and varying oil price levels and volatility, Vijay et al. (2002) concluded that R&D has a positive impact on the market value of oil and gas companies, although the effect is small.

In the valuation of corporate R&D expenditures, Szewcyk et al. (1996) showed a positive relation between a firm's Tobin's q (a ratio comparing a firm's market value to its book value) and its stock price reaction to announcements of increased R&D expenditures. Secondly, Samuel et al. (1996) revealed that spending on R&D, debt ratio, and institutional ownership were positively affecting stock returns. Thirdly, Chan et al. (2002) discovered that firms with high spending on R&D, relative to their market value, generate high excess returns in the future although they tend to have poor past returns. They concluded that spending on R&D has a positive significant relationship with stock prices.

However, there are also studies that highlight the negative aspects or limitations of R&D investments. Ali et al. (2012) concluded that the market often under-prices the benefits of R&D expenditures, indicating that investors may not fully appreciate the long-term value these investments can bring. This under-pricing can be attributed to the inherent uncertainties and risks associated with R&D, such as the potential for projects to fail, the lengthy timeframes needed to see results, and the difficulty in accurately predicting the commercial success of innovative products. Similarly, Kim et al. (2018) found that while R&D investments can have positive effects, the dominance of negative effects, such as financial constraints and misaligned market expectations, often lead to a decrease in firm value. Additionally, Zhang (2015) identified that R&D investments increase distress risk due to financial constraints, which negatively impacts firm value.

Relevance to AI investments

While this research focuses on the effect of AI investments on market value, understanding the dualities of R&D investments is relevant for several reasons. AI investments can be considered a specific type of R&D expenditure, given that AI development involves significant research and technological advancement. The mixed results from R&D investment studies highlight the importance of context, industry, and firm-specific factors in determining the market's response.

By examining R&D investments' impact on market value, this research can draw parallels to AI investments, providing a broader framework to understand how innovation-driven expenditures influence investor perceptions and market behaviour. Given the uncertainty and varying outcomes associated with R&D, this research aims to shed light on whether AI investments follow similar patterns or exhibit unique characteristics that set them apart from traditional R&D investments. Understanding these dynamics helps in framing AI investments within the larger context of R&D, emphasising the need for strategic planning and communication to maximise investor confidence and market value.

2.2.3 Short- and long-term effect

In the context of value creation, both the short-term and long-term effects are important for the assessment of a firm’s value. There is a difference between investing in innovation and actually creating value. Investors and managers have different priorities; managers must balance short-term performance with long-term strategic goals, while investors are looking for short-term financial return.

The immediate impacts of strategic decisions, such as investments in R&D, reflect current market reactions and investor sentiment. These short-term effects can be influenced by market conditions, news, and events. In the short-term, positive market reactions to R&D investments indicate investor confidence and optimism about the potential of these investments to drive innovation and provide a competitive edge. However, R&D expenses do not necessarily translate into increased firm value immediately. The expectation is that investors will recognise the potential of R&D-driven innovations to generate future growth, thereby increasing the firm’s market value over time (Lev & Sougiannis, 1996).

In the long-term, sustained positive market reactions suggest that investors anticipate profitability and long-term benefits from these R&D initiatives, validating their initial expectations. However, the benefits of R&D investments often do not materialise in the same year due to the complex phases of knowledge transfer, including acquisition, communication, application, acceptance, and assimilation (Falk, 2012). Therefore, it is logical to consider the time lag between incurring R&D expenditures and realising the benefits in terms of revenue generation. Chai (2012) explored the effect of lagged R&D expenditures, highlighting the need to understand the temporal dynamics of these investments. Chai (2012) found that the impact of R&D expenditures on firm performance is significant after a lag period, emphasising that immediate financial gains are often unrealistic due to the prolonged nature of R&D processes. This underscores the importance of patience and strategic long-term planning for firms engaging in R&D.

Moreover, Öztürk and Zeren (2015) investigated the Turkish manufacturing industry and found that the positive effects of R&D on firm performance, particularly sales growth, were more significant after one to two years. Similarly, multiple studies show that lagged R&D expenditures have a significant positive effect on income or firm performance, highlighting the delayed realisation of R&D benefits (Ferdaous & Rahman, 2017; Konak & Kendirli, 2016). This suggests the importance of considering temporal aspects in evaluating R&D effectiveness. Additionally, Ribeiro et al. (2016) found that current (same year) R&D expenditures have no statistically significant effect on firm market value, while one-year lagged R&D expenditures show a positive, significant correlation with firm market value.

To conclude, there is ongoing debate about the nature of the relationship between R&D investments and firm performance, whether it is linear or non-linear. Some studies suggest a linear relationship where increased R&D consistently leads to improved performance, while others propose a non-linear relationship, indicating diminishing or variable returns at different levels of investment (Czarnitzki & Hall, 2011). This underscores the importance of investigating both the short-term and long-term impacts of R&D investments to fully comprehend their role in value creation. As indicated by Ho et al. (2005), a period of greater than three years has two distinct disadvantages. First, since various economic, industry, and firm-specific factors may have influenced the firm's share prices in the intervening years, it is possible that the longer time period returns are not traceable to R&D expenditures. When assessing the influence of R&D expenditures, the effect gets noisier with increasing lag. Secondly, an extended duration may lead to a significantly smaller sample size and introduce a survivorship bias into the data set. Ho et al. (2005) measured a five-year lag; the results are qualitatively comparable to the three-year lag, but because of the significantly smaller sample size, they are not published. Therefore, a lag longer than three years is not favoured.

2.3 ARTIFICIAL INTELLIGENCE

The journey of AI unfolds across decades, marked by transformative milestones. In the 1950s, the nascent stages of AI development laid the foundational groundwork. McCulloch and Pitts’ model from 1943 describes a computer model used to learn based on a process comparable with neurons in the human brain (Muthukrishnan et al., 2020). Fast-forwarding to the 1980s, the advent of machine learning ushered in a new era, providing computers with the ability to learn without explicit programming. During this period, distinctions emerged between "strong AI," aspiring to possess a mind, and "weak AI," which focused on specialised tasks (Searle, 1980).

Defining AI involves understanding its constituent elements. The term "artificial" signifies creations made by humans, setting them apart from naturally occurring phenomena (Mikalef & Gupta, 2021). "Intelligence" within the AI context encompasses mental activities such as learning, reasoning, and understanding (Lichtenhaler, 2019). Accordingly, AI endeavours to make machines capable of simulating human intelligence, engaging in tasks that require cognitive abilities like understanding, reasoning, and problem-solving (Mikalef & Gupta, 2021). In other words, things that are artificially intelligent are distinct from those that are naturally intelligent because they are artefacts that possess special properties that non-artefacts typically lack. These are therefore objects that, as a result of a particular process (because they were made, designed, or produced in this manner), have a particular property (intelligence) (Fetzer, 1990).

Kaplan and Haenlein (2019) offer three stages of AI. The first stage is Artificial Narrow Intelligence (ANI), which are AI technologies capable of doing tasks in specific areas. It is defined as weak, below human-level AI. Examples of ANI are virtual assistants, search engines, self-driving cars, and voice recognition. Secondly, there is Artificial General Intelligence (AGI). In the future, AGI technologies may be capable of teaching themselves how to solve problems from new areas. It outperforms or equals humans in several areas. Therefore, it could solve problems autonomously for tasks they were never designed for. The final step in AI evolution is Artificial Super Intelligence (ASI), which are technologies that can solve problems in any area, faster and more accurately than a human could. ASI is the type of intelligence most often referred to in science fiction, where humanity is taken over by self-aware computers or robots.

2.3.1 Types of AI

Technology can exhibit different types of intelligence. According to Kaplan and Haenlein (2019), there are three types. Firstly, there is cognitive intelligence. These are competencies related to systematic thinking and pattern recognition. Secondly, there is emotional intelligence. This is the adaptability, emotional self-awareness, self-confidence, and achievement orientation. Thirdly, there is social intelligence. These are skills like empathy, inspirational leadership, and teamwork.

AI technologies that only show cognitive intelligence are classified as Analytical AI and are currently the most common type of AI. This type generates a cognitive representation of the world and uses learning based on past experience to inform future decisions. When a technology shows emotional intelligence in addition to cognitive intelligence, it is classified as Human-Inspired AI. These technologies can recognise human emotions and adapt their responses accordingly. For example, advanced vision systems to recognise emotions like joy, surprise, and anger at the same level as humans. Humanised AI is the third class, exhibiting all three types of intelligence. True Humanised AI does not exist yet. Such systems would be able to be self-conscious and self-aware in their interactions with others. Building AI systems that actually experience the world in a fundamental way are a project for the distant (potentially close) future. Note that the fourth class are human beings. Human beings consist of artistic creativity, which is not possible for AI to represent (Kaplan & Haenlein, 2019).

AI contributes to complex engineering and scientific workflows through supplementing, augmenting, or simulating human intelligence in an efficient and precise manner. Examples of such tasks are conversational bots used in customer service, fraud detection in banking, and precision diagnostics in healthcare (Muthukrishnan et al., 2020). There are two subsets of AI, which is illustrated in Figure 2. The first, Machine Learning (ML), becomes a pivotal technique. It trains machines to learn from data, empowering them to make inferences, predictions, and identify associations guiding decision-making (Afiouni, 2019; Wang et al., 2019). This process, often characterised by an inductive approach, involves identifying decision rules based on collected data through statistical methods (Schmidt et al., 2020). In short, ML is concerned with learning complex associations using data. Human experts select informative features to build these predictive models. Due to the availability of large amounts of data and computational power, a surge in successful applications of ML has emerged. Applications such as machine vision, natural language processing, robotics, and diagnostics (Muthukrishnan et al., 2020).

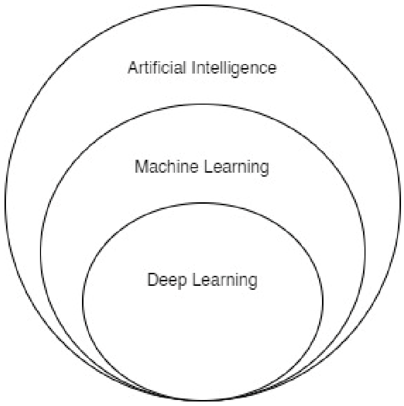


Figure 2. Artificial Intelligence and its subfields (Muthukrishnan et al., 2020)

Machine learning further branches into three categories: supervised learning, unsupervised learning, and reinforcement learning. Each category serves distinct purposes, from learning patterns with labelled data to discovering hidden patterns in datasets (Schmidt et al., 2020; Quinio et al., 2017). These categories shape the learning landscape and are used to train algorithms with training data sets. In supervised learning, a training data set consists of a number of observations of feature sets and their corresponding response variable. The algorithm learns which combinations of feature values correspond to specific values of the response variable, enabling it to predict the response variable when presented with unlabelled data. For instance, training an algorithm with employee data and their performance scores can help predict which job applicants will become high performers. Unsupervised learning, on the other hand, utilises unlabelled data sets to discover patterns or commonalities within the data. An example of this is analysing sales data to identify purchasing patterns that can optimise store layouts. In reinforcement learning, the algorithm learns to make decisions that maximise rewards over time based on feedback from its actions. For example, in marketing, reinforcement learning can be used to determine the best actions to maximise a customer's long-term profitability, using current information about the customer and the market (James et al., 2021).

A subset from ML is Deep Learning (DL), which is a more complex, multi-layered derivation of structures from data employing artificial neural network architecture. DL represents a significant advancement in AI capabilities. It refers to the methodologies that rely on deep neural networks. Neural networks were initially designed to simulate neural activities in a human brain. Therefore, the goal of deep learning and neural networks is to mimic the way human thinking works. It distinguishes itself from other prevailing machine learning methods in its ability to process unlabelled data. This means that it can process natural data in raw forms. To demonstrate a certain method of data gathering, data analysis, and algorithm development, deep learning is necessary (Wang et al., 2019). Firstly, a lot of different kinds of data need to be gathered so that deep learning can gain sufficient information (Najafabadi et al., 2015). Second, deep learning has turned analysis into an evidential and data-driven process (McAfee & Brynjolfsson, 2012). Third, by learning implicit decisions, deep learning techniques (such as neural networks) enable the computer to resemble a human (Bengio et al., 2013). Deep learning makes it possible for machines to make decisions instead of humans through these specific modifications, which may eventually lead to data and machine management replacing human and knowledge management. Consequently, deep learning makes businesses more machine- and data-driven and nimble (Wang et al., 2019).

2.3.2 Applications of AI

Looking at corporations, AI has already started to impact every single element of a firm's value chain and, in the process, transform industries in a fundamental manner, especially service industries (Huang & Rust, 2018). Building on the three classifications of AI, Kaplan and Haenlein (2019) illustrate examples how these are applied within corporations. Firstly, Analytical AI is applied by robo-advisors leveraging automation and AI algorithms to manage client portfolios. Secondly, Human-Inspired AI is applied by stores identifying unhappy shoppers via facial recognition at checkouts to trigger remedial actions. Thirdly, Humanised AI could be applied by virtual agents dealing with customer complaints and addressing concerns of unhappy customers.

In addition, within corporations AI applications are utilised at various departments. In Human Resource Management (HRM), to enhance the screening of CVs and the selection of candidates through advanced applicant tracking systems. In marketing and sales, AI enables improved targeting and personalised communication. AI systems can identify numerous psych types (Kosinski et al., 2013) and craft messages that align with individual preferences, resulting in tens of thousands of variations of the same message being deployed daily. In customer service, AI is implemented through chatbots that generate automatic responses to inquiries sent via social media channels or emails (Kaplan & Haenlein, 2019).

According to Haan (2023), businesses are using AI across a wide range of areas. The most popular application is customer service. Next to that, there is cybersecurity and fraud prevention, digital assistants, customer relationship management and inventory management. Businesses are improving their customer experience by using AI for instant messaging, to optimise emails, and for personalised services, such as product recommendations. Next to that, businesses leverage AI for long-form written content, including website text and tailored advertising. Additionally, AI is becoming more and more prevalent in phone handling. AI is finding its way into more and more channels of customer connection, making the whole customer experience more streamlined and customised.

2.4 INVESTING IN AI: A DUAL PERSPECTIVE

Navigating the complex landscape of AI, it is essential to consider both its positive and negative dimensions. Over the past decade, AI technologies have advanced significantly, finding widespread commercial applications and offering transformative possibilities (Furman & Seamans, 2019). This section explores the dual nature of AI, emphasising its potential benefits and the critical challenges that investors and firms must consider.

2.4.1 Positive effects of AI

AI, as a prediction technology, enables firms to learn better and faster from big quantities of data, potentially revolutionising business decision-making. This transformative capability positions AI as a general-purpose technology, fostering growth through heightened productivity and product innovation across diverse sectors (Aghion et al., 2017; Agrawal et al., 2019).

Technological change, driven significantly by AI, serves as a catalyst for investment opportunities and economic growth (Romer, 1990; Aghion & Howitt, 1992; Kogan et al., 2017).

One of the key takeaways is that as firms invest more in AI, there is a subsequent boost in product innovation, translating into higher growth. AI can increase business efficiency and create value. For instance, projected data for 2024 suggests that an average of 2.5 hours per employee can be saved every day due to AI implementations (Haan, 2023). This efficiency gain underscores the potential of AI to streamline operations and enhance productivity.

Many scholars have highlighted the broad impact of AI on various sectors. According to Aghion et al. (2017), AI's role as a general-purpose technology can lead to significant advancements in productivity and innovation, similar to the impact of electricity and the internal combustion engine in previous industrial revolutions. Agrawal et al. (2019) further argue that AI facilitates better decision-making processes and the development of new products, driving economic growth and transformation across industries.

A survey conducted by Davenport et al. (2017) involving 250 executives revealed that the primary goal of AI implementation was to improve existing products. The survey showed that 51% of executives mentioned enhancing the features, functions, and performance of their products as the main benefit of AI. Other significant benefits included making better decisions (35%), creating new products (32%), and optimising internal business operations (36%). Additionally, 36% of the executives highlighted freeing up workers to be more creative by automating tasks as a key advantage. This trend indicates that businesses leverage AI primarily to improve product offerings and streamline operations rather than as a tool for workforce reduction.

The benefits of AI span various areas, from internal sites for employee queries to health treatment recommendation systems and personalised customer interactions (Davenport et al., 2017). These applications demonstrate AI's potential to enhance both operational efficiency and customer experiences, thereby driving business growth and innovation.

2.4.2 Risks and challenges of AI implementation

Despite the promising benefits, AI implementation comes with significant risks and challenges that investors and firms should consider.

Financial and operational risks

The substantial costs associated with AI implementation are a significant concern for firms. These costs include not only the direct expenses of AI systems, but also project and consulting fees, system integration, upgrading expenses, transition costs, and the need for skill enhancement among existing employees (Bughin et al., 2018). The financial burden is considerable and can be a deterrent for firms considering AI investments.

Investing in AI is a long-term commitment. Unlike other technologies that may offer quicker returns, AI investments might take ten years or more to yield significant benefits, if they materialise at all (Corea, 2017). This long payback period increases the risk for investors, who may be concerned about the opportunity cost and the uncertainty of returns. Additionally, the inherent high risk of AI projects, coupled with the challenges in measuring the tangible benefits and payback time, makes AI a challenging undertaking (Lui et al., 2021; Bughin et al., 2018). Firms must be prepared for potential delays and setbacks, which can impact overall financial performance and investor confidence. Additionally, Mihet & Philippon (2019) highlight that the suggested benefits of AI may be over-hyped or may take much longer to materialise, adding another layer of risk for investors who might be overly optimistic about short-term returns.

For investors, these financial and operational risks translate into uncertainties regarding the ROI. The long-term commitment and high costs can make AI projects less attractive compared to other investment opportunities with quicker and more predictable returns. Investors are weighing these factors carefully. They consider the long-term potential against the immediate financial burdens.

Strategic and implementation challenges

As explained in Section 2.3, AI technology is complex and multifaceted, leading to significant strategic and implementation challenges. Identifying a firm's AI investments is difficult due to the diverse nature of AI applications. AI can manifest in various forms, from enhancing machinery through computer vision to introducing entirely new product lines. This diversity complicates the tracking and management of AI projects, adding layers of complexity to strategic planning and execution.

Firms express concern that machines, devoid of functions aligned with management goals, may make incorrect decisions, leading to potentially fatal operational mistakes (Lui et al., 2021). Such errors can result in significant reputational damage, revenue losses, and diminished public trust. Ensuring that AI systems are robust, reliable, and aligned with organisational objectives is a critical challenge that requires ongoing oversight and adjustment.

From an investor's perspective, these strategic and implementation challenges highlight the importance of due diligence. Investors need to thoroughly evaluate a firm's AI strategy, its execution capabilities, and the potential risks associated with specific AI projects. The complexity and potential for operational missteps mean that only firms with strong management practices and technical expertise are likely to succeed in AI implementation.

Ethical and social implications

While not the primary concern for many investors, ethical issues surrounding AI cannot be ignored. Examples of AI ethics issues include fairness, explainability, transparency, robustness, and privacy (Coeckelbergh, 2020). AI systems, if not properly managed, may unintentionally adopt biases present in large datasets, leading to hidden discrimination or unfair treatment (Duan et al., 2019; Shrestha et al., 2019).

Moreover, the potential for job losses or technological unemployment raises concerns among the workforce, leading to opposition against AI adoption (Jarrahi, 2018; Ransbotham et al., 2018). Balancing the benefits of AI with its social impact is a delicate task that firms must navigate carefully.

For investors, the ethical and social implications of AI can impact a firm's reputation and, consequently, its market value. Ethical failures or public backlash over job losses caused by AI can lead to negative publicity and potential regulatory challenges. Investors must consider these factors when assessing the long-term sustainability of AI investments.

2.4.3 Implications for investors and the market

Investment in AI, while promising, may face scepticism from investors as firms cannot easily prove its immediate benefits. This scepticism may render companies investing in disruptive technologies, including AI, financially unattractive in the short-term (Staw et al., 1981). Therefore, researchers have focused on determining whether AI technologies will ultimately benefit and add value to businesses, or whether they will have no effect at all. Few studies have used both qualitative and quantitative methods to evaluate the practical impact of AI on businesses.

The difficulty in evaluating AI investments lies in predicting the costs and benefits. According to Lui et al. (2021), the market's view on AI investments depends on whether the long-term benefits are expected to be greater than the immediate costs. If the future benefits outweigh the costs, the company's market value increases; if not, the market value decreases.

The effect of AI investments is difficult to measure. Makki and Abdallah (2019) were unable to determine the precise value spent by each company on R&D, mainly on AI investment. Therefore, they considered AI as a dummy variable, where AI investment is equal to zero when the company doesn't invest in AI in a specific quarter. They found that AI investment significantly and directly affects stock prices.

For investors, it's important to balance the large financial commitments and long waiting times for returns on AI projects with the potential market value gains (Bughin et al., 2018; Corea, 2017). Investors need to carefully check a company's AI strategy and ability to manage AI projects, as mistakes can hurt the company's reputation and market value (Lui et al., 2021). Ethical and social issues, like bias and job losses due to AI, can also affect public perception and regulatory scrutiny, impacting market value (Coeckelbergh, 2020; Duan et al., 2019).

This research helps investors understand these issues, aiding them in making better decisions about the benefits and risks of AI investments.

2.5 MEDIA ATTENTION

Understanding the market's reaction to AI investments is crucial for determining the overall impact of such technologies on firm value. This section explores how media attention can shape investor perceptions and subsequently influence market value, and why media attention is a relevant factor to consider.

2.5.1 Relevance of media attention

Media attention plays a significant role in shaping investor perceptions and can have a profound impact on a firm's market value. The media contributes to reducing information asymmetry between businesses and significant market participants by making information widely available to the public (Bushee et al., 2010). Enhanced information environments lead to better market efficiency and more informed investment decisions, ultimately benefiting firm value (Durnev et al., 2004).

Positive media attention can boost a firm's reputation and investor confidence. By making business activities and management decisions publicly known, the media can discourage managers from acting in their self-interest and encourage socially acceptable behaviour (Dai et al., 2015). This visibility can enhance the firm's market value by signalling competence and innovation to investors.

However, media attention can also have negative or neutral effects. First, the information gap between enterprises may not be effectively reduced by the media. Media coverage may be influenced by the interests of media outlets. They might be motivated to print gripping articles and dramatic news that will grab readers' attention, be less expensive to research, and result in a rise in circulation. News articles with this kind of drama and attention-grabbing potential exacerbate information asymmetry and make investors act irrationally. Second, the media might not be a useful watchdog over businesses' operations. The link between the media and the company being covered or the topic of managerial manipulation could be the cause of media coverage (Ahern & Sosyura, 2014).

Wang and Ye (2014) explored how media coverage of a firm's controlling shareholder influences firm valuation in China. They found that firms in which controlling shareholders receive more neutral media attention get higher valuation, whereas negative media reports on controlling shareholders impose adverse effects on firm valuation. Therefore, they found that favourable media coverage of the controlling shareholders does not improve firm value.

Moreover, Dang et al. (2020) found that media attention generally has a positive association with firm value, suggesting that increased visibility can enhance reputation and investor confidence. This underscores the importance of media attention in shaping market perceptions and its potential impact on firm value.

2.5.2 Measuring media attention

Quantifying media attention is essential for understanding its impact on market value and investor behaviour. In the context of AI investments, media attention can amplify the perceived significance of AI-related initiatives, influencing how investors react to such announcements. High media visibility can lead to increased scrutiny and interest from investors, which can drive stock price movements and affect market capitalisation.

By analysing media attention, this research aims to assess how the visibility and public perception of AI initiatives influence investor behaviour and market valuation. This is relevant because it provides insights into how external information sources shape market reactions, helping investors and firms understand the broader implications of their AI strategies.

Furthermore, understanding the role of media attention in AI investments can help firms manage their public relations strategies more effectively, ensuring that their AI initiatives are communicated in a way that maximises positive investor reactions. This can be crucial for firms looking to leverage AI for competitive advantage while maintaining strong investor confidence.

2.6 MARKET REACTIONS TO AI ANNOUNCEMENTS

Building on the understanding of media attention, this section delves into how specific AI-related announcements impact investor reactions and market value. Understanding the impact of AI announcements on market value is crucial for assessing how investors perceive the potential benefits and risks associated with AI investments. This section explores why it is relevant to measure market reactions at the moment of an announcement, especially in the context of AI, where investment details are often not publicly disclosed.

2.6.1 Relevance of measuring market reactions

Companies do not always disclose the exact amounts they invest in AI, making it challenging to evaluate the direct financial commitment and potential returns of these investments (Makki & Abdallah, 2019). Therefore, observing how the market reacts to AI announcements provides valuable insights into investor sentiment and the perceived value of these investments. The market's reaction to such announcements reflects the collective judgment of investors, who incorporate all available information, including expectations about future benefits and risks.

As explained in Section 2.1.2, the EMH suggests that asset prices fully reflect all available information, both current and anticipated future information (Fama, 1970). This means that when a company announces an AI investment, the market reaction should theoretically capture the expected future benefits and costs of that investment. Investors analyse the announcement, considering factors such as the potential for increased efficiency, innovation, and competitive advantage, as well as the associated risks and uncertainties (Lui et al., 2021).

Measuring the market reaction to AI announcements is particularly relevant because it provides a real-time assessment of how these investments are perceived. Positive market reactions can indicate investor confidence in the company's strategic direction and the potential value of the AI investment. Conversely, negative reactions may reflect concerns about the feasibility, cost, or potential impact of the AI initiative (Huang & Lee, 2023).

By examining market reactions, researchers and practitioners can gain insights into the effectiveness of AI investments and their alignment with investor expectations. This approach also helps identify the key factors that drive investor sentiment, such as the industry context, the company's technological capabilities, and the broader economic environment (Bushee et al., 2010).

2.6.2 Event study methodology

A common method in financial analysis is the event study methodology. The event study methodology is a powerful tool used to assess the impact of specific occurrences, such as AI announcements, on a firm's market value. This approach captures the immediate effect of an event on stock prices, providing a clear picture of investor reactions.

Management scholars have a potent tool at their disposal to investigate the degree to which managerial actions contribute to the development of value for the company (McWilliams & Siegel, 1997). An event study is a suitable method for this research since the stock market response happens instantly and can represent investors' expectations of future corporate performance. Even in less-than-ideal circumstances, the event study allows to quantify the instantaneous effect of a firm's actions without having to wait for the effect estimation of its accounting measures, which might not be available for several months (Bose & Pal, 2012).

An event study calculates the effect of a certain occurrence on a firm's value using data from the financial markets. Such a study is valuable because, in a rational market, changes in an event's impact will immediately affect the price of securities. As a result, using security prices recorded over a brief period of time, an estimate of the event's economic impact can be created. On the other hand, measurements directly connected to production can need months or even years of monitoring (MacKinlay, 1997). Event studies have a long history and have been refined over time, enabling researchers to separate the impact of specific events from other market movements, thus providing a clear picture of the event's effect on market value.

Lui et al. (2021) conducted an event study to provide empirical evidence about the market value of AI. Their research analysed 119 announcements from 62 listed firms and found that AI investment generally has a negative impact on firm market value, with stock prices decreasing by an average of 1.77% on the announcement day. This effect was more pronounced in nonmanufacturing firms and those with weak IT capabilities or low credit ratings. The findings suggest that investors perceive AI investment announcements as negative news for the majority of firms, likely due to the high costs and risks associated with AI adoption and implementation.

Conversely, Huang & Lee (2023) employed an event study to capture the abnormal returns resulting from the announcement of AI implementation. Their study revealed that AI implementation announcements could lead to both positive and negative abnormal returns, depending on the context and characteristics of the firms making the announcements. For instance, firms with robust IT infrastructure and those in industries more likely to benefit from AI showed positive abnormal returns, while others experienced declines in stock value.

By using the event study methodology, this research aims to capture the market reactions to AI-related announcements, providing valuable insights into how investors perceive the value of these investments. This information can help firms better understand the market dynamics at play and adjust their strategies to maximise investor confidence and market value.

2.7 HYPOTHESES

As explained in the introduction (Section 1), this study employs a structured methodology akin to a funnel to explore the impact of AI investments on market value. This approach systematically narrows the focus from broad R&D investments to specific AI-related media attention and, finally, to individual AI announcements. This section outlines the hypotheses that guide this research, making clear the connections between the literature review and the empirical investigation.

The funnel approach is chosen to address the complexity of measuring AI investments and their impact on market value. By starting with a broad analysis of R&D investments, the study establishes a foundation for understanding how general innovation activities influence market perceptions. Moving to media attention, the study examines the role of external narratives in shaping investor behaviour. Finally, by focusing on specific AI announcements, the research captures the immediate market reactions, providing detailed insights into investor sentiment.

2.7.1 Hypothesis 1: R&D investments and market value

The first part of the study examines the relationship between R&D investments and firm market value. The literature has demonstrated that R&D investments drive innovation, leading to new products and processes that provide a competitive edge (Cohen & Levinthal, 1990). These investments are often perceived by investors as a signal of a firm’s commitment to future growth and technological advancement, which can enhance market value (Sougiannis, 1994). However, the relationship between R&D spending and market value is not always straightforward. Factors such as industry type, firm size, and the overall economic environment can influence this relationship.

R&D expenditures encompass a wide range of activities, including basic research, applied research, and development. Each of these activities contributes differently to a firm's innovation capacity and, consequently, its market value. Basic research, for example, focuses on generating new knowledge without immediate commercial applications, while applied research and development are more directly related to creating marketable products and processes (Link, 1982). The spillover effect, where companies benefit from the innovations of others, further complicates the analysis. Firms with higher R&D spending are often better positioned to capitalise on external innovations (Lev & Sougiannis, 1996).

In the context of AI, R&D investments are particularly relevant given the substantial resources required for AI development and implementation. Firms with higher R&D expenditures, including investments in AI, are expected to experience positive market reactions due to the anticipated future benefits of these innovations. According to the EMH, the market value of a firm should reflect a higher growth when investing in R&D (Fama, 1970). Ehie and Olibe (2010) further support this by finding a positive effect of R&D investment on firm market value.

Section 2.2.3 of the literature review highlights the dualities of R&D investments, noting that while R&D can lead to significant innovations and competitive advantages, it also involves substantial risks and uncertainties. The literature presents mixed results regarding the short-term and long-term effects of R&D investments on market value. Some studies have shown that R&D expenditures positively affect market value, but these benefits often materialise over a longer period due to the time required for innovation processes to yield results (Sougiannis, 1994). Conversely, other studies suggest that the market may underprice the benefits of R&D investments in the short-term due to the inherent uncertainties and risks involved (Ali et al., 2012).

Positive short-term effects of R&D investments would reflect investor confidence and optimism regarding the potential of these R&D investments to drive innovation and competitive advantage. But, these short-term effects might not always be immediately visible in firm market value due to the time lag between investment and the realisation of commercial benefits. In the long-term, positive market reactions would indicate that investors expect profitability and long-term benefits from AI initiatives, which would validate their initial expectations. Successful R&D efforts can lead to substantial increases in market value as new products and technologies developed through R&D reach the market and generate revenue.

This study aims to investigate whether this positive relationship between R&D investments and market value holds, considering both short-term and long-term effects. By understanding these dynamics, the research provides a comprehensive view of how R&D expenditures influence firm valuation over time. The first hypothesis is as follows:

H1: Firms investing in R&D will witness a positive impact on their market value in the period from 2013 to 2023, both in the short-term and long-term.

2.7.2 Hypothesis 2: Media attention and market value

The second part of the study explores the effect of media attention on the market value of firms. Media coverage can significantly influence investor perceptions and confidence, consistent with the signaling theory (Connelly et al., 2011). Positive media attention can enhance a firm's reputation and attract investor interest, while negative coverage can have the opposite effect. Media attention serves as a crucial intermediary between broad R&D investments and specific AI announcements, influencing how the market interprets and reacts to AI initiatives.

Media plays a dual role in shaping public perception and market behaviour. It reduces information asymmetry by making company activities more visible to investors (Bushee et al., 2010). Enhanced visibility can lead to increased investor confidence and higher market valuations. However, media coverage can also introduce biases, emphasising sensational stories over substantive information (Ahern & Sosyura, 2014). This duality highlights the importance of examining media attention in the context of AI investments.

Section 2.5 of the literature review discusses how media attention can amplify or mitigate the perceived value of AI investments. Studies have shown that media coverage can affect stock prices by shaping investor perceptions (Bushee et al., 2010; Ahern & Sosyura, 2014). Research by Dang et al. (2020) showed that media coverage is positively associated with firm value, suggesting that increased media visibility can enhance a firm's reputation and investor confidence. However, Wang and Ye (2014) found that favourable media attention focused on controlling shareholders does not necessarily improve firm value, indicating that the impact of media attention can vary.

In the context of AI, media attention is particularly relevant given the public's fascination with technological advancements and the potential of AI to transform industries. Positive media coverage of AI initiatives can signal to investors that a firm is at the forefront of technological innovation, potentially leading to increased market value. Conversely, negative media attention can raise concerns about the risks and uncertainties associated with AI investments. Therefore, positive media attention can create a favourable environment for firms, leading to increased investor interest and higher market valuations. On the other hand, negative media coverage can have a detrimental effect on market value by highlighting potential risks and uncertainties.

This study aims to investigate the impact of media attention on market value, considering the potential for both positive and negative effects. By understanding these dynamics, the research provides insights into how external narratives shape investor behaviour and market perceptions of AI investments. The second hypothesis is as follows:

H2: Firms experiencing more media attention related to AI activities will witness a positive impact on their market value in the period from 2013 to 2023.

2.7.3 Hypothesis 3: Market reaction to AI announcements

The third part of the study delves into the immediate market reactions to AI-related announcements. Using the event study methodology, which captures the instantaneous effect of specific events on stock prices, the study analyses 110 AI-related announcements from five listed companies. This approach provides insights into how investors respond to AI initiatives in real-time, reflecting their expectations about the potential benefits and risks associated with these investments.

The event study methodology is particularly relevant for this research because it isolates the impact of specific announcements from other market movements. This method allows for a precise measurement of the market's immediate reaction to AI initiatives, offering a clear view of investor sentiment and market dynamics (MacKinlay, 1997). Given the mixed results in the literature regarding the market reaction to AI announcements, this study seeks to provide a clearer understanding of investor sentiment.

Section 2.6 of the literature review highlights the importance of event studies in capturing market reactions to specific announcements. Studies have shown that market reactions to AI announcements can vary depending on the context and characteristics of the firm. Lui et al. (2021) conducted an event study to provide empirical evidence about the market value of AI. Their findings suggest that investors perceive AI investment announcements as negative news for the majority of firms, likely due to the high costs and risks associated with AI adoption and implementation. Therefore, the effects of AI on businesses were not as favourable as expected in this study. On the other hand, Huang & Lee (2023) employed an event study to capture the abnormal returns resulting from the announcement of AI implementation. Their study revealed mixed results, depending on the context and characteristics of the firms making the announcements. For instance, firms with robust IT infrastructure and those in industries more likely to benefit from AI showed positive abnormal returns, while others experienced declines in stock value.

Positive market reactions to AI announcements can indicate investor confidence in the strategic direction of the company and the potential value of the AI investment. Conversely, negative reactions may reflect concerns about the feasibility, cost, or potential impact of the AI initiative. According to the EMH, the market value of a firm should reflect all available information, including the expected future benefits of current investments (Fama, 1970). This means that when firms announce AI initiatives, investors incorporate their expectations about the long-term profitability and strategic advantages of these investments into the stock price immediately. Therefore, the immediate market reaction also projects the anticipated long-term benefits of AI initiatives as perceived by investors.

By examining these reactions, the study aims to capture the nuanced perspectives of investors regarding AI investments. This study aims to provide detailed evidence on investors' reactions to AI initiatives, including their perspectives on the long-term benefits of these investments. The third hypothesis is as follows:

H3: Positive announcements regarding AI activities of firms will correspond with an increase in market value in the period from 2013 to 2023.

3. RESEARCH METHODOLOGY

In the research methodology chapter of this study, the theoretical framework, data collection methods, and analytical techniques used to extract, process, and analyse the data are explained.

As explained, this study employs a structured methodology, similar to a funnel, to explore the interplay among R&D investments, media attention surrounding AI, and more specifically, AI announcements, in shaping the market value of firms.

It highlights the importance of innovation in helping companies improve, get a competitive advantage, and create value. Subsequently, the study examines whether the media "hype" around AI leads to positive market perception. Finally, five case studies are done regarding the market reaction of five companies on the announcement of the implementation of AI. The research spans the period from 2013 to 2023 and for each step within the process, a selection of companies is made to find the effect of one of the three variables on market value. The research model of the funnel methodology is shown in Figure 3.

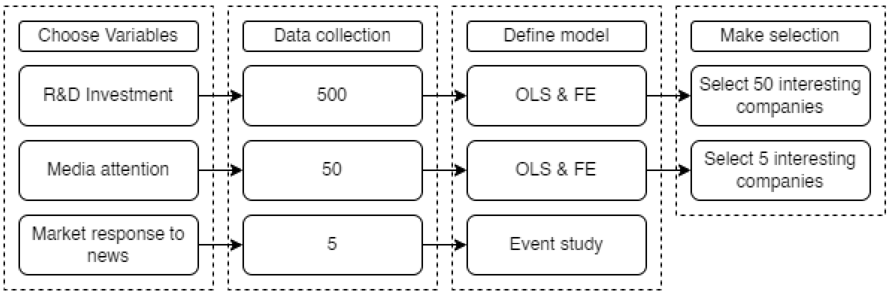


Figure 3. Research model

3.1 RESEARCH & DEVELOPMENT

Initially, a large sample encompassing 500 firms from the United States (U.S.) is employed to assess the overall impact of R&D investments on market value. Given that AI is a crucial component within the broader spectrum of R&D, this phase aims to establish a foundational understanding of the relationship between R&D expenditures and market value. To approach this, for the period from 2013 to 2023 data is gathered from publicly listed companies from the Standard and Poor's 500 Index (S&P 500). This index represents a significant proportion of the U.S. economy and includes companies across all sectors.

The index is calculated by aggregating the adjusted market caps of each company and dividing this total by a divisor, a unique figure set by the index manager of the S&P 500. This divisor is adjusted for corporate actions such as mergers, stock splits, or other structural changes within the index's components to ensure that such events do not alter the numerical value of the index. Thus, the index serves as a stable, comparative measure of market trends over time, useful for investors and funds aiming to replicate market returns or compare their performance against a market benchmark (Frino & Gallagher, 2001).

When investors refer to the stock market going up or down, they often look at the performance of indexes like the S&P 500 as a benchmark. It provides a broad, snapshot indicator of stock market trends, reflecting the collective value of its constituent stocks. The S&P 500 operates as an index of the 500 largest companies listed on stock exchanges in the U.S. For this research, the snapshot is taken on the 1st of May, 2024. The names and Reuters Instrument Codes (RICs) of the 500 companies encompassing the S&P 500 on this day are retrieved.

The primary objective of this part of the study is to investigate the impact of R&D investments on firm value. As explained in Section 2.2.3 from the literature review, Sougiannis (1994) suggested that the benefits of R&D investments are often realised over varying periods of time, reflecting both short-term market reactions and long-term profitability improvements. Therefore, the study aims to capture both the immediate and delayed effects of R&D investments on firm value.

Firstly, immediate market reactions, where investors often respond quickly to announcements of R&D investments, reflecting confidence in the firm's future potential. This immediate effect is captured by the current year's R&D investment. Understanding this can help firms communicate their R&D activities more effectively to investors to optimise stock market reactions. Secondly, medium-term realisation (one-year lagged) is relevant because the initial outcomes of R&D projects, such as prototype development or early-stage innovations, typically emerge in the medium term. Capturing this effect helps to assess whether early-stage results from R&D activities translate into tangible benefits for the firm, aiding in evaluating the efficiency and effectiveness of R&D processes. Thirdly, long-term maturity (three-year lagged) is relevant because significant R&D projects often take few years to mature fully and impact firm profitability and market value. By studying the long-term effects (three years), the sustained benefits of R&D investments and their contribution to the firm's strategic goals and competitive advantage can be explained. Other researchers have used other methods, such as amortisation. This method spreads the impact of R&D spending over multiple periods based on an assumed rate of depreciation (Chan et al., 2001). Lagged variables directly include past values of R&D expenditures in the regression model to capture delayed effects and it is not needed to assume depreciation rates, which is why in this study lagged variables are used.

3.1.1 Variables

Using the database of Refinitiv Eikon, the financial data of the S&P 500 companies are retrieved. For the analysis, R&D expenditures are used as the independent variable. Using the market values of these 500 companies from the period 2013 to 2023, the effect of the independent variable on the market capitalisation, which functions as the dependent variable, is investigated. The dependent variable, market capitalisation, includes an immediate effect as well as two lagged effects to make sure the effect is both measured on the short-term as well as on the long-term.

Independent Variable: R&D Investment

The independent variable in this study is the total amount of funds allocated by publicly listed companies within the S&P 500 towards R&D activities. This variable is measured as the ratio of R&D expenditures to the total net sales (revenue) of the firm. This approach, as recommended by Ehie and Olibe (2010), is preferred over using the absolute level of R&D spending. The rationale is to normalise R&D investments relative to the firm's revenue, mitigating the confounding effects of firm size on market performance. Larger firms typically have more resources to invest in R&D; however, the goal of this study is to isolate the impact of R&D intensity on market value, independent of firm size. By using this proportional measure, the effectiveness of R&D investments across firms of varying sizes can be more accurately assessed.

Dependent Variable: Market Capitalisation

The dependent variable in this study is the market capitalisation of publicly listed companies within the S&P 500 index. Market capitalisation is a measure of corporate size, calculated as the product of the number of shares outstanding and the share price. For this analysis, market capitalisation is deflated by the total sales (revenue) of the firm. This adjustment allows for a normalised comparison across firms by accounting for differences in firm size. By using this deflated measure, the relationship between market value and R&D investments, independent of the absolute size of the firms, can be better captured (Ehie & Olibe, 2010).

To capture the effects of R&D investments over the different time horizons, the following variations of the dependent variable are included:

- **Immediate effect**: The market capitalisation measured in the same year as the R&D investment.

- **Medium-term effect**: The market capitalisation measured one year after the R&D investment.

- **Long-term effect**: The market capitalisation measured three years after the R&D investment.

Control Variables

To accurately assess the relationship between R&D investments and market capitalisation, other variables are controlled for in the analysis. This approach helps in isolating the effect of R&D expenditures from other factors that could influence the market value of the firms. Using the Refinitiv Eikon database, the values of three control variables are retrieved. The control variables sector, firm size, and leverage are in line with several other studies (Ho et al., 2005; Ehie & Olibe, 2010), which are summarised below:

- **Sector**: Different sectors have different norms for R&D spending and market capitalisation growth. Therefore, including sector as a categorical variable can help control for these sector-specific effects. This is a categorical variable, which is equivalent to having one intercept per sector. One sector is taken as the baseline, helping to avoid perfect multicollinearity. This assumes that between sectors, the relationship between the dependent and independent variables is the same, but with a different mean for each group.

- **Firm size**: Larger companies have both higher market capitalisations and more resources to allocate R&D expenditures. Therefore, the total assets reported is used as proxy for company size to control for the firm size effects.

- **Leverage**: The capital structure of the companies is included as a control variable to account for how leverage may affect a company's valuation and investment capacity in R&D expenditures. Therefore, the debt-to-equity ratio of the companies is used to control for these effects. This represents a proxy for firm risk and controls for cross-sectional variation in firm valuation due to differences in capital structure.

3.1.2 Model

The methodology involves conducting a regression analysis where the dataset consists of yearly observations for each company over the 11-year period. This approach allows for observing dynamics over time and understanding the persistency or changes in R&D investment impacts. The models used are an Ordinary Least Squares (OLS) analysis and a Fixed-Effects (FE) analysis. Unlike the OLS analysis, the FE analysis incorporates fixed effects and firm-specific effects into the regression model. Firstly, the fixed effects, or time effects, control for all macro-level changes affecting all companies in the same way during specific time periods, such as economic cycles and industry influences. Secondly, the firm effects are used to account for all unobserved heterogeneity that is unique to each company but constant over time. These might include intrinsic characteristics such as corporate culture, management style, brand value, or strategic positioning that are not explicitly measured but can influence a firm's market capitalisation and investment decisions.

To incorporate the lagged effects, the model includes the impact of R&D expenditures from the previous year and three years prior. This is achieved by introducing lagged independent variables, specifically $R\&D_{it-1}$ and $R\&D_{it-3}$, to capture the delayed effects of R&D investment on market capitalisation. By doing so, the analysis accounts for both the immediate impact and the longer-term influence of R&D activities on firm value. Also, as suggested by prior research (Ho et al., 2005; Ehie & Olibe, 2010), this regression model includes a squared term for R&D intensity (R&D deflated by revenue) to control for potential non-linear effects of R&D on market value. The models are specified as follows:

OLS Regression model

$$MARKETCAP_{it} = \beta_0 + \beta_1 * R\&D_{it} + \beta_2 * R\&D\text{^}2_{it} + \beta_3 * R\&D_{it-1} + \beta_4 * R\&D_{it-3} + \beta_5 * SIZE_{it} + \beta_6 * LEV_{it} + \beta_7 * SECTOR_i + \varepsilon_{it}$$

FE Regression model

$$MARKETCAP_{it} = \beta_0 + \beta_1 * R\&D_{it} + \beta_2 * R\&D\text{^}2_{it} + \beta_3 * R\&D_{it-1} + \beta_4 * R\&D_{it-3} + \beta_5 * SIZE_{it} + \beta_6 * LEV_{it} + \beta_7 * SECTOR_i + YEAR\_FE_i + FIRM\_FE_i + \varepsilon_{it}$$

Where:

$MARKETCAP_{it}$ = The market capitalisation of company i in year t, measured as the market capitalisation deflated by revenue.

$R\&D_{it}$ = The R&D investments of company i in year t, measured as the R&D expenditures deflated by revenue.

$SIZE_{it}$ = The total assets of company i in year t, used as a proxy for company size.

LEV_{it} = The debt-to-equity ratio of company i in year t.

$SECTOR_i$ = The sector category of company i, treated as a categorical variable.

$YEAR\_FE_i$ = Year fixed effects capture common external shocks or trends affecting all companies in the same manner across different years, such as macroeconomic conditions or industry-wide regulatory changes.

$FIRM\_FE_i$ = Year fixed effects capture common external shocks or trends affecting all companies in the same manner across different years, such as macroeconomic conditions or industry-wide regulatory changes.

ε_{it} = The error term for company i in year t, capturing unobserved influences on market capitalisation.

3.1.3 Assumptions

In applying the regression analysis, several assumptions are taken into account to ensure the reliability and validity of the findings.

First, the linearity assumption is important as it posits that the relationship between the dependent variable, market capitalisation, and independent variables such as R&D investments and firm size, is linear. This assumption underpins the model's specification and the interpretation of the regression coefficients. To verify linearity, diagnostic plots are employed to visually inspect any systematic patterns that might suggest nonlinear relationships.

> **Null hypothesis (H_0):** The relationship between the dependent variable (market capitalisation) and the independent variable (R&D investments) is linear.
>
> **Alternative hypothesis (H_1):** The relationship between the dependent variable and the independent variable is not linear.

Second, the assumption of no perfect multicollinearity is essential. It ensures that none of the independent variables used in the model is an exact linear combination of any other variables. This condition is crucial for accurately estimating the model coefficients, as perfect multicollinearity would prevent from isolating the individual effect of each independent variable. Multicollinearity is tested by examining the Variance Inflation Factor (VIF) for each predictor; a VIF value exceeding 10 is typically considered indicative of serious multicollinearity concerns.

> **Null Hypothesis (H_0):** There is no perfect multicollinearity among the independent variables.
>
> **Alternative Hypothesis (H_1):** There is perfect multicollinearity among the independent variables.

Third, the model presumes the independence of observations. While the data inherently involves observations that are grouped by entities (firms) across time, the model is designed to handle this structure explicitly through firm effects and year effects. However, the assumption extends to the expectation that the error terms across these groups are independent, a condition vital for the standard errors of the estimates to be valid. This is addressed by testing for serial correlation in the residuals using the Durbin-Watson test.

> **Null Hypothesis (H_0):** The residuals are independent across observations.
>
> **Alternative Hypothesis (H_1):** The residuals are not independent across observations.

Lastly, homoscedasticity is assumed, meaning that the error terms are expected to have a constant variance across all observations. If this assumption does not hold, it could lead to inefficient estimates and biased standard errors, which might distort hypothesis tests. To test for homoscedasticity, the Breusch-Pagan test is used.

> **Null Hypothesis (H_0):** The residuals have constant variance (homoscedasticity).
>
> **Alternative Hypothesis (H_1):** The residuals do not have constant variance (heteroscedasticity).

3.2 MEDIA ATTENTION

For the second part of the study, the objective is to investigate the relationship between media attention, measured by the number of AI-related announcements, and the market value of publicly traded companies. Initially, a descriptive analysis of the variables is performed to explore the data distribution and basic correlations between these variables. Following this, a regression analysis is conducted to delve deeper into the nature of this relationship.

For this analysis, the same data as in the first part of the research is used but it focuses on a subset of 50 companies from the S&P 500 that stood out in the data related to R&D. These companies are selected based on the following criteria, ensuring a representative sample:

- **Diverse sectors**. Ensuring representation across various sectors to encompass industry-specific dynamics in the analysis. From the dataset encompassing the S&P 500, a diverse range of sectors is included the media attention dataset.

- **Firm sizes.** Including a range of company sizes, from small to large, to capture diverse dynamics and impacts on market value. A wide range of firm sizes is included in the dataset.

- **Reported R&D expenditures.** Including those companies that have reported their R&D expenditures, ensuring consistency with the first part of the study. Without this information, these companies were not included in the model regarding the relationship between R&D expenditures and market value. Therefore, these should also not be included in this part.

The number of news announcements is retrieved from the NexisUni database. This is an online research tool widely used by academics, journalists and business professionals to access a vast collection of news articles. It offers an extensive database of sources from around the world. In the context of academic research methodology, the database serves as a valuable resource for gathering and analysing data related to news coverage, legal cases, industry trends, and business developments. The research platform made for students from NexisUni is a very complete platform that contains a trustworthy online news archive which goes to 40 years back in time. It has various functions in its search engine to find the news articles needed for this research. It is available via the University of Twente. This research uses the following search criteria for the number of published news articles:

- **Company:** The NexisUni database offers the function to find the name of a specific company and use this as a search criterium. For each company, one specific company name is chosen (instead of including the names of subdivisions).

- **AI**: To look whether a news announcement is made regarding AI, the NexisUni database offers the function to find articles related to "Artificial Intelligence". The database itself can distinguish articles about AI, including words like machine learning.

- **Year**: For each search, the date from the 1st of January until the 31st of December per year is used as search criterium.

- **Source:** Exclude sources not directly contributing to the understanding of market reactions or investor sentiment, including:

    - Lab Reviews/Journals, Legal Documents, and Administrative Materials: Excluded due to their lack of relevance to market analysis.

    - Stock Stories and Promotional Content: Publications and headlines focused on stock movements or promotional content were excluded to avoid bias. This includes sources such as "global round up", "news bites", "aap newsfeed", and others that primarily serve market news or promotional purposes.

    - Specific Financial Terms and Headlines: Excluded to maintain focus on relevant news. Terms such as "financial ratings", "market open", "financial results", and others related to financial analyst recommendations and stock performance were excluded.

- **Grouping:** NexusUni offers the function to group double articles. These are news articles with "reasonable similarity". It chooses the document in each group as the 'lead document', which is the most current document.

3.2.1 Variables

The independent variable in this relationship is media attention. Data on the number of AI-related announcements by publicly traded companies within a specific year is gathered. Next, the market value data for the same set of companies and corresponding years is obtained. This is the dependent variable and can be retained from the dataset also used in the first part of this research. In short:

Independent Variable: Media Attention

The independent variable is the number of AI announcements made by publicly listed companies within a given year. Media attention is measured as the ratio of the number of news announcements in a year to the total net sales (revenue) of the firm. This approach is preferred over using the raw number of news announcements, because this mitigates confounding effects of firm size on market performance. Larger firms typically receive more media attention in general, but the goal of this study is to isolate the impact of media attention on market value, independent of firm size. By using this proportional measure, the effectiveness of media attention across firms of varying sizes can be more accurately assessed.

Dependent Variable: Market Capitalisation

The dependent variable in the second part of this study is the same as in the first part, market capitalisation of publicly listed companies. For this part, only the selection of 50 companies is relevant, of which market capitalisation is a measure of corporate size, calculated as the product of the number of shares outstanding and the share price. For this analysis, the market capitalisation is deflated by the total sales (revenue) of the firm. This adjustment allows for a normalised comparison across firms by accounting for differences in firm size. By using this deflated measure, the relationship between market value and R&D investments, independent of the absolute size of the firms, can better be captured (Ehie & Olibe, 2010).

Control variables

To accurately assess the relationship between media attention and market capitalisation, the same control variables described in Section 3.1.1 are used, which are also used by prior studies (Ho et al., 2005; Ehie & Olibe, 2010). These include:

- **Sector**
- **Firm size**
- **Leverage**

3.2.2 Model

The methodology involves conducting a regression analysis where the dataset comprises yearly observations of each company over the 11-year period. This approach allows for observing dynamics over time and understanding the persistency or changes in media coverage of AI implementations. The analysis uses both OLS and FE models. As well as described in Section 3.1.2, fixed effects and firm-specific effects are incorporated into the FE model to control for macro-level changes and unique company influences. Also, as suggested by prior research (Ho et al., 2005; Ehie & Olibe, 2010), this regression model includes a squared term for R&D intensity to control for potential non-linear effects of R&D on market value. The regression models are specified as follows:

OLS Regression model

$MARKETCAP_{it} = \beta_0 + \beta_1 * MEDATT_{it} + \beta_2 * R\&D_{it} + \beta_3 * R\&D\text{^}2_{it} + \beta_4 * SIZE_{it} + \beta_5 * LEV_{it} + \beta_6 * SECTOR_i + \varepsilon_{it}$

FE Regression model

$MARKETCAP_{it} = \beta_0 + \beta_1 * MEDATT_{it} + \beta_2 * R\&D_{it} + \beta_3 * R\&D\text{^}2_{it} + \beta_4 * SIZE_{it} + \beta_5 * LEV_{it} + \beta_6 * SECTOR_i + YEAR\_FE_i + FIRM\_FE_i + \varepsilon_{it}$

Where:
$MEDATT_{it}$ = The media attention AI-related news announcements for company i in year t, measured as the number of news announcements deflated by revenue.
Other variables : As previously defined, see Section 3.1.2.

3.2.3 Assumptions

The assumptions underlying the regression analysis in this section of the study on media attention and market value are consistent with those described in Section 3.1.3. For a detailed discussion of these assumptions - including linearity, independence of residuals, homoscedasticity, absence of perfect multicollinearity, and normality of residuals - refer to that section. Also, the same null and alternative hypotheses are used for this part of the study. This consistency ensures that the methodologies applied across different parts of the study are comparable.

3.3 MARKET RESPONSE TO NEWS

This study will further delve into the specific context of AI investments. This final phase of the research aims to pinpoint and analyse the relationship between the announcement of AI investments and the market value of firms within the subset of five companies out of the S&P 500. The intention is to unravel nuanced patterns and correlations, providing a comprehensive understanding of how AI investments contribute to the market value of companies in the business landscape. The aim is to find news articles that show companies willing to invest in AI, and see whether this has an effect on its market value.

The logic underlying the hypothesis is the belief that investors in capital markets process publicly available information on firm activities to assess the impact of these activities, not just on current performance but also the performance of the firm in future periods. When new information about a company's operations that could have an impact on its earnings in the present and the future is made public, the stock price of the company adjusts fairly quickly to reflect the current valuation of the company (Fama, 1970). The method's strength is that it captures the collective opinion of many investors regarding the discounted value of the firm's performance in the present and the future that may be attributed to certain occurrences. This opinion is reflected in the stock price and the market value of the firm, as explained in Section 2.6.2.

3.3.1 Data collection

From the dataset regarding media attention, and consisting of 50 firms, five companies are chosen to conduct in-depth analysis. These five companies are selected based on the following criteria:

- **Sector diversity:** To get a good understanding of the effect on market value of AI announcements, the firms should represent varying sectors and branches within these sectors. This ensures that there is coverage across various industry dynamics and their unique responses to news.

- **Market capitalisation:** Include firms of varying sizes to ensure that there is coverage across various firm sizes and market capitalisations and their unique responses to news.

- **R&D intensity:** Firms with high or low R&D expenditures might respond differently to news, especially if the news is related to technological or product advancements related to AI. Therefore, include varying R&D intensities.

- **Media attention:** For this event study that specifically targets AI news announcements, ensuring a sufficient and relatively uniform level of media coverage related to AI across the chosen firms is important. This will help maintain consistency in the availability of data and the impact analysis of AI-related news.

To get the right data, it is defined what constitutes an AI implementation announcement. For the purpose of this study, an AI implementation announcement is defined as *any public disclosure by the company that involves the adoption, development, or enhancement of AI technologies*. The goal of this implementation is to impact the company’s operations, products, or services. The criteria for inclusion of these news announcements, to ensure that only material announcements likely to influence investor perceptions and behaviours are considered, are:

- **Specific information:** The announcement should contain specific information about the nature of the AI implementation, expected impact, and any financial commitments involved.

- **New information:** The announcement should be identified as containing new information that has not been previously reported or factored into the company's stock price.

- **Timing:** The announcement must be strategically chosen to represent different phases within the study's timeframe, from 2013 to 2023. This ensures a temporal spread that captures the evolution of the impact of AI technologies over time. For each year, two AI-related news announcements are collected.

After recording the date of the announcement, the stock price data is collected. This includes the daily returns of each stock for the period from 01-01-2013 to 31-12-2023. The daily returns are calculated as the $price_{t+1}$ / $price_t$.

To avoid distortions in price analysis, the data is adjusted for splits, dividends, and other corporate actions. Therefore, the market index is used to isolate the specific effect of an event on a company's stock price for broader market movements. Since the five companies that are analysed are all in the S&P 500 index, this index is chosen as the market index. The broad index makes it easier to compare results across different sectors since the same benchmark is used for all companies. It captures overall market trends and sentiments, which is useful for understanding how these external factors impact the companies relative to the market as a whole.

3.3.2 Model

As explained in Section 2.6.2 from the literature review, the statistical method used to quantify the influence of events like AI announcements on stock prices is called the event study. The fundamental idea is to separate the impact of two different kinds of information on stock prices: information unique to the company in question (such as a dividend announcement) and other data that could have an impact on market-wide stock prices (such as changes in interest rates) (Mitchell & Netter, 1994).

In this study, the market model is used to control for market-wide effects and isolate the firm-specific impact of AI announcements. By comparing the stock returns around the event date to a benchmark (S&P 500 index), the abnormal returns attributable to the AI announcement are estimated.

The event window chosen for this study spans ten days, encompassing the days before the announcement (including day 0, which is the day of the announcement), four days before, and five days after the event. This window is selected to capture both the immediate reaction of the market to the new information provided by the AI announcement and any potential lagged effects that may occur a few days later. For instance, some investors may receive and react to the news announcement later than others.

The inclusion of the days before the announcement is critical for several reasons. First, it allows the study to account for any anticipatory trading that might occur if investors have prior knowledge or expectations of the announcement. Such trading can influence stock prices before the actual event, reflecting market sentiment and information leaks that can affect the validity of the results if not considered. This anticipatory effect is a common phenomenon in financial markets where investors try to position themselves ahead of significant corporate events, which is indicated by for example an upward trend before the announcement day.

By using a five-day event window, this study aligns with common standards in financial event studies, which suggest that this duration is effective in capturing the complete market response to significant corporate announcements. The five days after the event help capture the immediate market reaction and any adjustments that occur when investors act on the new information. Studies such as MacKinlay (1997) support the use of this window length to ensure that both anticipatory trading before the event and adjustments after the event are correctly measured.

The procedure involves the following steps:

1. **Estimate Normal Performance:** The normal or expected performance of the stock in the absence of the event is determined. This is done by estimating the relationship between the stock and the market index.

2. **Calculate Abnormal Returns:** Abnormal returns are calculated as the difference between the actual stock returns and the expected returns predicted by the market model.

3. **Aggregate Abnormal Returns:** The cumulative abnormal returns (CARs) are computed by summing the abnormal returns over the event window. This provides a measure of the total impact of the event on the stock price.

Using this information, the results are plotted. The plots in the results section illustrate the CARs for each of the five companies around their respective AI announcement dates. These plots can help visualise the market's reaction to the announcements and provide insights into how AI investments affect firm value across different sectors and characteristics. By focusing on the graphical representation of the CARs, a clear and intuitive understanding of the market's response to AI announcements is given. The plots show whether there is a significant positive or negative reaction, how quickly the market adjusts, and any differences in reactions across firms with varying sizes, R&D intensities, and media coverage.

4. DATA

This chapter presents and describes the samples used to investigate the hypotheses. The sample involves (a selection of) the companies from the S&P 500, retrieved on the 1st of May, 2024. To systematically investigate the impact of AI investments on the market value of publicly traded companies, a structured approach is adopted. In Section 4.1, the first part of the study is examined by looking at the data regarding the analysis of the effect of firms' R&D expenditures on market value. In Section 4.2, the second part is explained regarding the selection of 50 companies. Finally, the sample and data regarding the five case companies are discussed in Section 4.3.

4.1 RESEARCH & DEVELOPMENT

4.1.1 Sample

The initial phase of the research involves gathering data on R&D investments made by publicly listed companies within the S&P 500 index. This data is crucial for assessing the overall impact of R&D activities on market value. The data collection process entails obtaining information on the total funds allocated by these companies towards R&D activities over the period from 2013 to 2023. The data is obtained from Refinitiv Eikon.

First of all, all the companies currently in the S&P 500 are included. Since this is a passive fund, this means that it automatically contains the 500 largest publicly traded firms in the U.S. The data is obtained from the index on the 1st of May, 2024. Although it is called S&P 500, the dataset contains 503 entities. This is because it can list multiple share classes from the same corporation. Each share class might have different voting rights, dividend policies, or other features, and they are treated as separate entities within the index (Bodie et al., 2021). Accordingly, the dataset shows that three firms have multiple entries, which indicates they have multiple share classes included in the S&P 500. These are:

- **Alphabet Inc**: Alphabet typically has Class A and Class C shares listed. Class A shares (GOOGL) carry voting rights, whereas Class C shares (GOOG) do not. This distinction allows the company's founders to retain significant control over the company while still raising capital through public markets.

- **Fox Corp**: Fox Corp has Class A and Class B shares. Class A shares are common stock with regular voting rights, usually one vote per share. Class B shares often have enhanced voting rights, such as ten votes per share, allowing certain groups (like founding families or executives) to maintain greater influence over corporate decisions.

- **News Corp**: News Corp also has Class A and Class B shares, just like Fox Corp. The same applies here.

Figure 4 illustrates the distribution of firms within the S&P 500 across various sectors, highlighting the prominence of each sector in the S&P 500. The Technology sector leads with over 75 firms, reflecting its crucial role and rapid growth in the modern economy. Following closely, the Industrials and Consumer Cyclicals sectors, with around 70 and 65 firms respectively, highlight the importance of manufacturing, construction, and consumer-driven markets. The Healthcare sector, with approximately 60 firms, indicates a strong presence due to the increasing demand for medical innovations. The Financials sector, comprising about 55 firms, underscores its vital role in economic stability. Consumer Non-Cyclicals, with around 50 firms, suggests steady demand for essential goods. The fewer firms in Utilities, Real Estate, Basic Materials, and Energy sectors, ranging from about 25 to 30, reflect specialised markets with higher entry barriers and significant capital requirements.

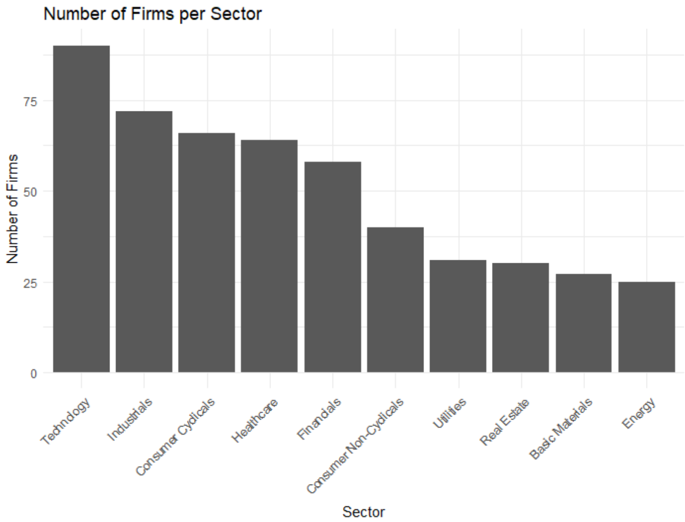


Figure 4. Number of firms per sector from the S&P 500, retrieved on May 1st, 2024

After retrieving the data from the Refinitiv Eikon database for the research period for the specific companies, there are missing values in the data. Not every firm from the S&P 500 publishes its financial information regarding R&D expenditures. This is quite common, because not for every industry R&D spending is a significant part of the business model and/or critical to the growth. Figure 5 showcases this, highlighting significant differences in how different sectors allocate resources to innovation. The Consumer Cyclicals sector leads with the highest average R&D investments, surpassing 4 billion dollars, indicating a strong focus on developing new products and responding to market trends. The Technology sector follows with substantial investments exceeding 2 billion dollars, reflecting the high importance of continuous innovation in maintaining competitive advantage. Healthcare and Industrials sectors also show considerable R&D investments, around 1 billion dollars, emphasising their need for ongoing research and development to drive medical advancements and industrial innovations. In contrast, sectors like Energy, Consumer Non-Cyclicals, Basic Materials, Utilities, Real Estate, and Financials demonstrate significantly lower average R&D investments, often below 500 million dollars. These lower investments may be due to the nature of their industries, where innovation is less frequent or occurs through other forms of capital expenditure rather than traditional R&D.

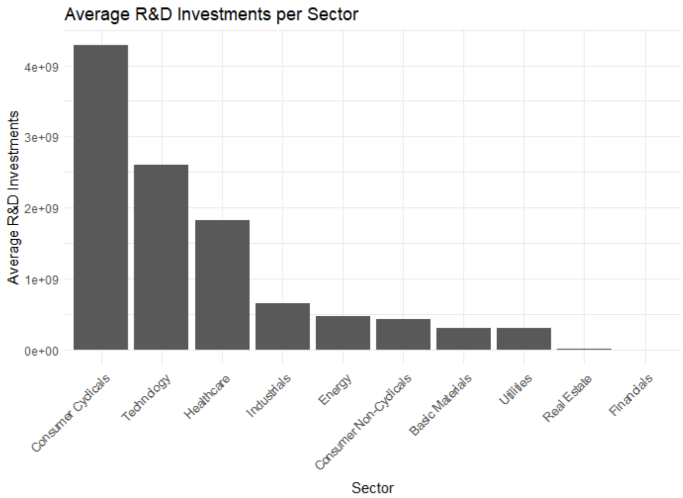


Figure 5. Average R&D expenditures per sector from the S&P 500, retrieved on May 1st, 2024

4.1.2 Descriptive statistics

To avoid any compounding effects, natural logarithms are used which are directly interpretable as approximate proportional differences. This not only makes the data closer to a normal distribution, but it also results in easier interpretation of results because it represents relative changes in the original metric (Ehie & Olibe, 2010). Next to that, the data is winsorized at the 1 and 99 percentile. This makes sure that outliers are removed from the dataset. Lastly, missing values are excluded from the dataset and the data in these rows is not used when running the model.

Table 1 summarises the descriptive statistics of the dataset containing 503 U.S. listed firms and 5,533 firm-year observations (503 firms multiplied by 11 years). The variables analysed include Market Capitalisation (MARKETCAP), R&D expenditures (R&D), Firm Size (SIZE), and Leverage (LEV). The Sector (SECTOR) control variable is excluded from the table as it is categorical.

Descriptive statistics

Variable	*N*	*Mean*	*Sd*	*Min*	*25%*	*Median*	*75%*	*Max*
MARKETCAP	4977	0.64	0.50	-0.59	0.32	0.63	0.96	1.94
R&D	2143	-1.28	0.57	-2.94	-1.60	-1.17	-0.84	-0.32
SIZE	5446	10.31	0.62	8.85	9.89	10.29	10.69	11.98
LEV	4935	-0.13	0.52	-2.16	-0.37	-0.11	0.15	1.15

Table 1. Descriptive statistics including R&D expenditures

The average market capitalisation is 0.64 with a standard deviation of 0.50, indicating moderate variability around the mean. The median market capitalisation is 0.63, suggesting a relatively symmetrical distribution. This indicates that on average, firms from the S&P 500 index have a slightly positive market performance over the period studied. The positive mean suggests that these firms are generally performing well in the market, likely due to robust business models, strong competitive positions, and effective management strategies. The minimum value of -0.59 indicates that some firms experienced a decrease in market value, while the maximum value of 1.94 suggests significant market value growth for other firms. The range of -0.59 to 1.94 shows considerable variability in market performance among the firms in the sample. This suggests that while many firms are performing well, there are some firms experiencing declines in market value, indicating the presence of poorly performing firms within the S&P 500 index.

R&D expenditures have a mean of -1.28 and a standard deviation of 0.57, indicating substantial variability around the mean. A negative log value indicates that the original, non-log-transformed value was between 0 and 1. The negative mean value suggests that, on average, firms invest a smaller proportion of their revenue in R&D. The median is -1.17, slightly higher than the mean, indicating a left-skewed distribution. The values range from -2.94 to -0.32, indicating that while most firms invest relatively low amounts in R&D compared to their revenue, some firms invest significantly more, which could indicate a strategic emphasis on innovation in those firms. This disparity suggests that while innovation is a priority for some firms, others may focus their resources elsewhere. This is also indicated in Figure 5, which shows that in some sectors there are way less R&D expenses compared to other sectors.

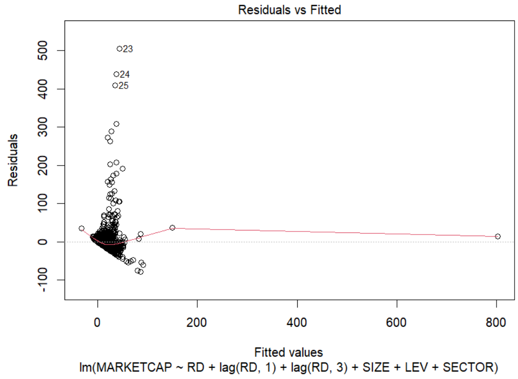
Firm size shows a mean of 10.31 and a standard deviation of 0.62, indicating a fairly consistent size among the firms in the sample. The median size is 10.29, suggesting a symmetrical distribution. The values range from 8.85 to 11.98, indicating that the firms in the sample are relatively large, with most firms having comparable sizes. This consistency in firm size suggests that the sample is representative of large, established companies that typically make up the S&P 500 index. This makes sense as the S&P 500 index comprises large-cap firms that are leaders in their sectors.

Leverage has a mean of -0.13 and a standard deviation of 0.52, showing moderate variability around the mean. The median is -0.11, close to the mean, indicating a somewhat symmetrical distribution. The values range from -2.16 to 1.15, suggesting that most firms have more equity than debt, which can be a sign of financial stability. The negative mean leverage implies that, on average, firms have a conservative capital structure, favouring equity over debt. This conservative approach can help firms avoid financial distress during economic downturns. The negative values for leverage indicate that the log-transformed leverage ratios were less than 1 in their original scale, reflecting low leverage levels. However, the wide range of leverage values indicates that some firms have significantly higher debt levels relative to their equity, reflecting diverse capital structures and risk profiles within the sample. This variability is logical as different industries have different capital requirements and risk tolerances, leading to varying leverage levels.

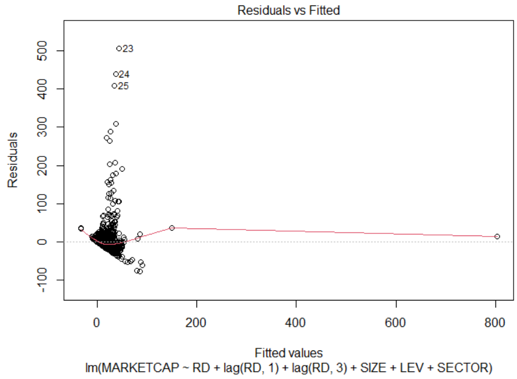
4.1.3 Assumptions check

Linearity Assumption

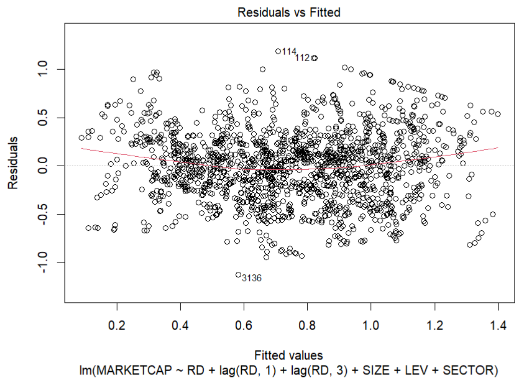
Firstly, linearity is checked between the dependent variable and the independent variables. For this, a diagnostic plot is employed to visually inspect any systematic patterns. This is done via the residuals vs fitted values plot and is shown in Figure 6.



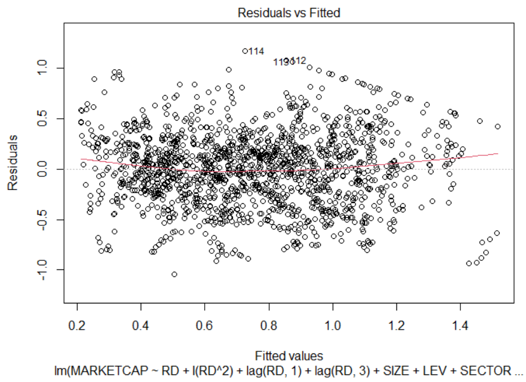
a) Residuals vs fitted plot without adjustments



b) Residuals vs fitted plot including logarithmic measure



c) Residuals vs fitted plot winsorized



d) Residuals vs fitted plot including squared term

Figure 6. Residuals vs fitted plots

Figure 6a shows that the residuals are concentrated near zero, with a few large outliers. This indicates potential issues with linearity, particularly at the lower level of the fitted values. In Figure 6b, the logarithm of the variables are taken. However, the transformation did not effectively address the underlying issues of linearity, as the residuals graph remains largely unchanged. This suggests that the logarithmic transformation was insufficient to correct the linearity issues present in the data. Therefore, in Figure 6c the data is winsorized at the 1 and 99 percentile. Improvements are visible compared to the prior model, but there are still patterns indicating remaining non-linearity. Lastly, the model in Figure 6d shows further improvement compared to Figure 6c, with the residuals more randomly scattered. As indicated in Section 3.1.2, a squared term of R&D is added to the model. This significantly improves model fit, but slight patterns may still be present. The Residuals vs Fitted plot shows that the residuals are more evenly distributed around the zero line, indicating that the model effectively captured the non-linear relationship. To conclude, the null hypothesis (H_0) of linearity is accepted.

Multicollinearity

The VIF for each predictor are shown in Table 2. A VIF value exceeding 10 is considered indicative of serious multicollinearity concerns. Based on the VIF values provided in Table 2, none of the predictors exhibit serious multicollinearity concerns. The highest VIF values are for R&D and R&D^2, which are 6.17 and 5.12, respectively. These values are well below the threshold of 10, indicating that multicollinearity is present but not at a level that would be considered problematic. Therefore, the null hypothesis (H_0) of no perfect multicollinearity is accepted.

Multicollinearity VIF values

Variable	*VIF*
R&D	6.17
$R\&D^2$	5.12
$R\&D_{t-1}$	3.61
$R\&D_{t-3}$	2.29
SIZE	1.01
LEV	1.06
SECTOR	1.06

Table 2. Multicollinearity test VIF values

Independence of observations

To test whether the model presumes the independence of observations, the Durbin-Watson test is conducted. The results are shown in Table 3. The DW statistic is very close to zero, indicating strong positive autocorrelation in the residuals. The P-Value is extremely small, which strongly rejects the null hypothesis of no autocorrelation. Therefore, positive autocorrelation violates the assumption of independence of errors in the model. This can lead to inefficient estimates and understated standard errors, which in turn can affect hypothesis tests. Therefore, the null hypothesis (H_0) of independence of observations is violated. To correct for this issue, this study will use robust standard errors. Robust standard errors adjust for autocorrelation and heteroscedasticity, providing more reliable estimates.

Durbin-Watson test

DW Statistic	0.23879
P-Value	2.2e-16

Table 3. Durbin-Watson test results

Heteroskedasticity

To test whether the error terms have a constant variance across all observations, the Breusch-Pagan test is conducted. The results are shown in Table 4. The BP statistic is 243.53, with an extremely small P-Value indicating that the null hypothesis (H_0) of homoscedasticity, or constant variance, is strongly rejected. Therefore, using robust standard errors can also improve this assumption by improving the reliability of the regression results.

Breusch-Pagan test

BP Statistic	243.53
P-Value	2.2e-16
df	14

Table 4. Breusch-Pagan test results

4.2 MEDIA ATTENTION

The second phase focuses on capturing media attention related to AI investments. Data on the number of AI-related announcements made by publicly traded companies within specific years is collected. These announcements include press releases, news articles, and other media sources that indicate a company's commitment to investing in AI technologies.

4.2.1 Sample

The number of news announcements regarding AI is retained from NexisUni. For every one of the 50 firms, the count of results, or news publications/articles, from the database for every year from 2013 to 2023 are retained. This is based on the search criteria described in Section 3.2.

Figure 7 illustrates the distribution of the sectors in the selection of 50 firms from the S&P 500. The Technology sector dominates the selection, with over 25 firms, indicating a strong emphasis on the technology industry within the sample. This reflects the sector's rapid growth and crucial role in driving innovation and economic development. The Healthcare sector follows with around 10 firms, highlighting its importance due to the continuous demand for medical advancements and services.

The Energy, Industrials, Consumer Non-Cyclicals, Basic Materials, and Consumer Cyclicals sectors each have fewer firms, ranging between 3 to 5 firms per sector. This distribution suggests that while these sectors are important, they are less represented in this particular selection of 50 companies. The relatively lower number of firms in these sectors may indicate lower media attention regarding AI or lower R&D intensity, as observed in the first part of the study. For example, the first part showed that sectors like Technology and Healthcare had significant R&D investments, correlating with their higher representation here.

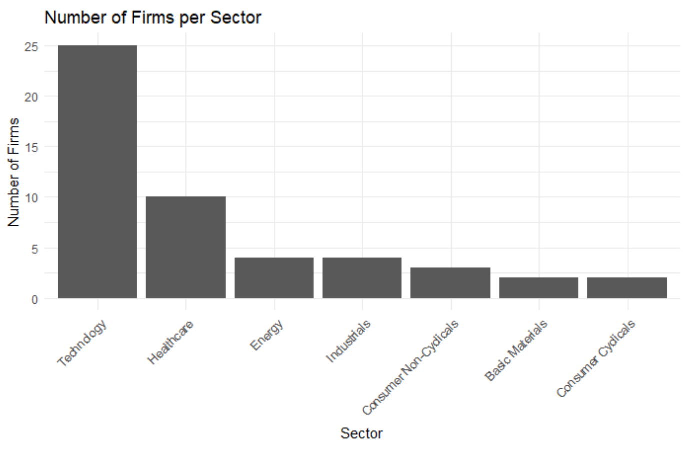


Figure 7. Number of firms per sector from the selection of 50 companies

Figure 8 shows the average number of AI announcements per year. From the plot, it is evident that AI media attention has fluctuated over the years. Notably, there appears to be a significant increase in AI announcements starting around 2016, peaking in 2018. This trend likely reflects growing interest and investment in AI technologies during these years, possibly driven by advancements in machine learning, natural language processing, and other AI fields. However, a slight decline in 2019 suggests a potential shift in media focus or a temporary slowdown in AI-related activities. This could be due to various factors, such as market saturation, regulatory challenges, or shifts in technological priorities. 2023 shows a remarkable spike, which is likely due to significant advancements in AI technology, particularly the development and adoption of large language models like ChatGPT. These models have captured the public's media attention, highlighting the transformative potential of AI in various sectors.

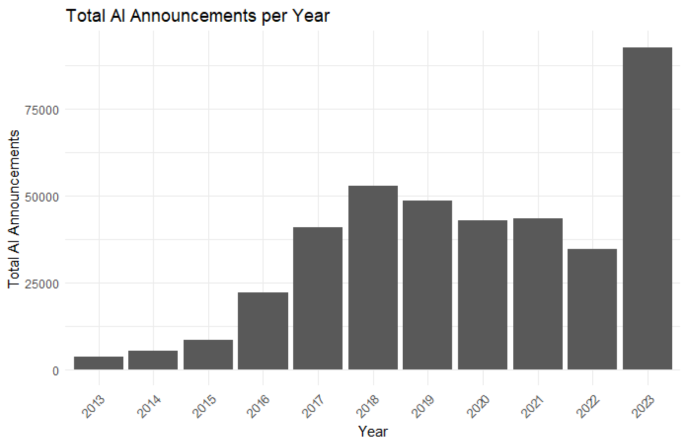


Figure 8. AI Announcements per year from the selection of 50 companies

4.2.2 Descriptive statistics

As well as in Section 4.1.2, natural logarithms are used which are directly interpretable as approximate proportional differences. This not only makes the data closer to a normal distribution, but it also results in easy interpretation of results because it represents relative changes in the original metric (Ehie & Olibe, 2010). Next to that, the data is winsorized at the 1 and 99 percentile. Lastly, missing values are excluded from the dataset.

Table 5 shows a diverse range of companies chosen from the dataset, focusing on the relation between media attention (MEDATT) and market capitalisation. The market capitalisation, R&D expenditures, and firm size differ because of the changed composition of the firms. The sample includes 550 firm-year observations (50 firms multiplied by 11 years), reflecting a broad spectrum of company profiles. Uber Technologies Inc. does not have its financial information published in the year 2013, which is why at least one observation is missing.

Descriptive statistics

Variable	*N*	*mean*	*sd*	*min*	*25%*	*median*	*75%*	*max*
MARKETCAP	549	0.86	0.51	-0.16	0.50	0.80	1.12	2.44
MEDATT	498	-8.54	0.93	-11.62	-9.20	-8.58	-7.92	-6.39
R&D	539	-1.14	0.52	-2.79	-1.38	-0.99	-0.77	-0.30
SIZE	549	10.40	0.60	9.24	9.93	10.44	10.89	11.57
LEV	498	-0.23	0.51	-2.15	-0.46	-0.21	0.09	0.92

Table 5. Descriptive statistics including media attention

The average market capitalisation is 0.86 with a standard deviation of 0.51, indicating moderate variability around the mean. The median market capitalisation is 0.80, suggesting that most firms cluster below the average. This indicates that, on average, firms in this sample have experienced positive market performance, with a mean value higher than the first part of the study (0.64). The minimum value of -0.16 and the maximum value of 2.44 suggest that while most firms have positive market values, a few firms have a significantly higher market capitalisation, skewing the distribution upwards. Compared to the first part, the slightly higher mean market capitalisation suggests that this subset includes some of the larger and better-performing firms from the S&P 500 index. This is not unexpected, since better-performing firms mostly receive more media attention and are able to invest more in innovation.

Media attention has a mean of -8.54 and a standard deviation of 0.93, with a median of -8.58. The negative values result from the log transformation of the number of news announcements relative to company revenue, indicating generally low media attention. The range from -11.62 to -6.39 shows significant variability, suggesting that some firms receive very little media coverage relative to their size, while others receive more. This variability may be due to differences in firm activities, public interest, and media strategies. Media attention shows only 498 observations because some firms in some years did not have any news articles published about AI, leading to these observations being left out. This is a common practice in data analysis to ensure the relevance and accuracy of the dataset, as including zero values for media attention might distort the analysis and lead to misleading conclusions.

R&D expenditures have a mean of -1.14 and a standard deviation of 0.52, with a median of -0.99. The negative mean value (resulting from log transformation) suggests that, on average, firms invest a smaller proportion of their revenue in R&D. The values range from -2.79 to -0.30, indicating that while some firms invest heavily in R&D, most firms have relatively lower expenditures. Compared to the first part of the study, where the mean R&D expenditure was -1.28, this subset shows a slightly higher average investment in R&D, suggesting that the firms from this selection invest more in R&D, which means that they have a focus on innovation.

Firm size shows a mean of 10.40 and a standard deviation of 0.60, indicating a relatively tight distribution around the average firm size in log terms. The median size is 10.44, suggesting a symmetrical distribution. The range from 9.24 to 11.57 indicates some variability, but it is less pronounced than market capitalisation, indicating more consistency in firm sizes within this sample. This is consistent with the first part of the study, where the mean firm size was 10.31, indicating that the selected subset still represents large, established companies typical of the S&P 500 index.

Leverage has a mean of -0.23 and a standard deviation of 0.51, with a median of -0.21. The negative mean leverage implies that, on average, firms have a conservative capital structure, favouring equity over debt. The range from -2.15 to 0.92 suggests diverse financial strategies among firms, from conservative to more aggressive leverage positions. Compared to the first part of the study, where the mean leverage was -0.13, this subset shows a slightly more conservative approach to leverage, possibly reflecting a cautious financial strategy among these firms.

4.2.3 Assumptions check

Linearity Assumption

Again, linearity is checked via the Residuals vs. fitted plots. The model, as explained in Section 3.2.2, is shown in Figure 9. The plot indicates that the linear regression model for market capitalisation is reasonably well-fitted, but a slight upward trend in the residuals suggests that the model might not be fully capturing the linear relationship between the predictors and the dependent variable. There is a slight spread of residuals at higher fitted values, indicating minor concerns with homoscedasticity, but it is not severe. A few labelled points suggest potential outliers or influential observations. While the model includes a quadratic term for R&D, slight curvature in the residuals suggests that some non-linear relationships might not be fully captured. Since there is only slight curvature, the null hypothesis (H_0) of linearity is accepted.

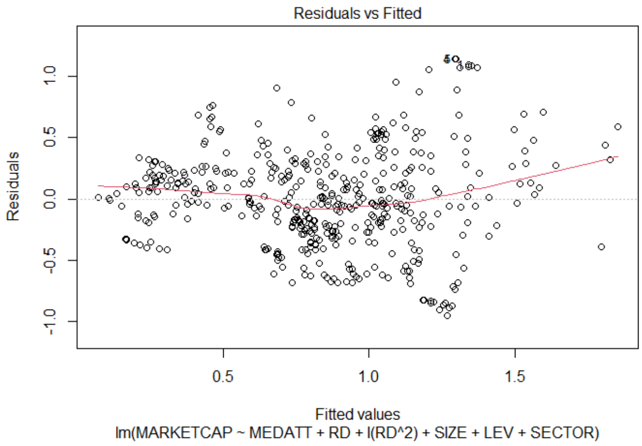


Figure 9. Residuals vs Fitted plot Selection Model

Multicollinearity

The VIF for each predictor is shown in Table 7. As none of the predictors is exceeding the limit of 10, no serious multicollinearity concerns exhibit. The highest VIF values are for R&D and R&D^2, which are 5.42 and 5.08, respectively. These values are well below the threshold of 10, indicating that multicollinearity is present but not at a level that would be considered problematic. Therefore, the null hypothesis (H_0) of no perfect multicollinearity is accepted.

Multicollinearity VIF values

Variable	*VIF*
MEDATT	1.28
R&D	5.42
R&D^2	5.08
SIZE	1.10
LEV	1.10
SECTOR	1.09

Table 6. Multicollinearity test VIF values selection

Independence of observations

The results of the Durbin-Watson test are shown in Table 7. The DW statistic is very close to zero, indicating strong positive autocorrelation in the residuals. The P-Value is extremely small, which strongly rejects the null hypothesis (H_0) of independence of observations. To correct for this issue, this study will use robust standard errors. Robust standard errors adjust for autocorrelation and heteroscedasticity, providing more reliable estimates. Therefore, also in this model robust standard errors are used, providing more reliable estimates.

Durbin-Watson test	
DW Statistic	0.2462
P-Value	2.2e-16

Table 7. Durbin-Watson test results selection

Heteroskedasticity

The results of the Breusch-Pagan test are shown in Table 8. The BP statistic is 87.065, with an extremely small P-Value indicating that the null hypothesis (H_0) of homoscedasticity, or constant variance, is strongly rejected. Therefore, using robust standard errors can also improve this assumption by improving the reliability of the regression results.

Breusch-Pagan test	
BP Statistic	87.065
P-Value	6.253e-14
df	11

Table 8. Breusch-Pagan test results

4.3 MARKET RESPONSE TO NEWS

The final phase involves a descriptive analysis of AI-related news events. This entails identifying and categorising AI-related events or news releases from the collected dataset. Using NexisUni, news items are found that are related to specific keywords needed for this final phase. After finding these relevant articles, the contents are systematically scanned indicative of AI adoption, development, partnerships, investments, or product launches.

Based on the criteria described in Section 3.3.1, the following five firms are chosen for further investigation:

- NVIDIA Corp (Technology): Already a major player in AI through their GPU developments and deep learning technology.

- Johnson & Johnson (Healthcare): In healthcare, AI can be transformative in areas like drug discovery and patient diagnostics.

- Tesla Inc (Consumer Cyclicals): Tesla's use of AI in autonomous driving technology makes it a prime candidate for studying the market reactions to AI news in the automotive sector.

- Cisco Systems Inc (Technology): Cisco leverages AI to enhance network security, optimise IT operations, and improve user experiences.

- Amazon.com Inc (Consumer Cyclicals): Amazon uses AI to personalise shopping experiences, streamline logistics, and develop new products.

Some further details about these companies van be found in Table 9. This showcases that this selection complies to the criteria described in Section 3.3.1: the sectors are diverse, it includes firms of varying sizes, the R&D intensity differs, and all companies have sufficient media coverage to find at least two AI-related news announcements per year.

Company	*Sector*	*Branche*	*AI applications*	*Firm size*	*Market capitalisation*	*R&D intensity*	*Minimal media coverage*
NVIDIA Corp	Technology	Semiconductors	GPU developments, deep learning	65.7B	3.24T	0.14	22
Johnson & Johnson	Healthcare	Pharmaceuticals & Biotech	Drug discovery, patient diagnostics	0.17T	0.35T	0.18	8
Tesla Inc	Consumer Cyclicals	Automotive	Autonomous driving technology	0.11T	0.57T	0.04	4
Cisco Systems Inc	Technology	Networking & Communication	Network security, IT operations, user experiences	0.10T	0.18T	0.13	68
Amazon.com Inc	Consumer Cyclicals	E-commerce	Personalised shopping, logistics, product development	0.53T	1.91T	0	40

Table 9. Company information market response to news (numbers from December 2023)

4.3.1 News announcements

110 news announcements are collected from the NexusUni database. For each year, two news announcements are chosen for further investigation. One example of a collected news announcement per company can be found in Table 10 on the next page.

Company	*Event date*	*Article title*	*Description*
NVIDIA Corp	5-4-2016	NVIDIA Launches World's First Deep Learning Supercomputer	Today, the NVIDIA(R) DGX-1(TM) is unveiled. The world's first deep learning supercomputer to meet the unlimited computing demands of artificial intelligence.
Johnson & Johnson	2-5-2018	Johnson & Johnson Vision Introduces Artificial-Intelligence Powered Virtual Assistant for Contact Lenses	Johnson & Johnson Vision today introduced Andy, a virtual assistant chatbot powered by AI. Andy is designed to help guide U.S. consumers throughout their ACUVUE Brand Contact Lens journey.
Tesla Inc	20-10-2016	All Tesla cars will be equipped for self-driving	Tesla Motors announced that its electric cars will be the first in the nation to all be fitted with the hardware they need to drive themselves.
Cisco Systems Inc	28-10-2014	US Patent Issued to Cisco Technology on Oct. 28.	Method and apparatus for detecting malicious software using machine learning techniques.
Amazon.com Inc	2-12-2020	AWS Announces Five Industrial Machine Learning Services	AWS announced Amazon Monitron, Amazon Lookout for Equipment, the AWS Panorama Appliance, the AWS Panorama SDK, and Amazon Lookout for Vision. Together, these five new machine learning services help industrial and manufacturing customers embed intelligence in their production processes in order to improve operational efficiency, quality control, security, and workplace safety.

Table 10. Examples of collected news announcements for the study

4.3.2 Interpretation

Using the daily returns of the five companies from the period 2013 to 2023, the event study is applied. For this, a list of firms with associated dates, and returns data for these firms are obtained. The data consist of three datasets:

Event dates

This dataset consists of two columns. The first column is the name of the unit of observation which experienced the event. The second column is the event date. Therefore, this dataset consists of 110 rows. For each row one event date and two events per company.

Stock price returns

This dataset is a time series of daily returns. The returns are measured in percent, i.e. a value of +4 is returns of +4%. The dataset has five columns of returns data: one for each unit of observation, which is a firm.

Index daily returns

Since there is a loss of statistical efficiency that comes from fluctuations of stock prices that have nothing to do with firm level news, adjustment of the returns data is resorted by including a market model. The market index captures market-wide fluctuations, which have nothing to do with firm-specific factors. This dataset also consists of two columns, one for the dates and one for the daily returns of the market index: the S&P 500.

5. RESULTS

This chapter presents the results for the three hypotheses. Firstly, the results regarding the effect of R&D investments on market value are tested. After discussing the correlations between the variables, the regression results are discussed, as well for the immediate effect as the lagged effects. Secondly, the results regarding the effect of the number of news announcements, or media attention, on the market value are tested. Also here, the correlation matrix as well as the regression results are discussed. For both the first and the second part, the results of the OLS and the FE model are interpreted. Thirdly, the results of the event study are tested, discussed, and interpreted.

5.1 RESEARCH & DEVELOPMENT

This section presents the results of the analysis focusing on the impact of R&D investments on firm market value. The analysis begins with the correlation matrix, which is examined to understand the relationships between variables, particularly the link between R&D expenditures and market value. The results of the regression analysis are then detailed, revealing the short-term and long-term effects of R&D investments on market capitalisation.

5.1.1 Correlation matrix

Table 11 presents the correlation matrix, which provides insight into the relationships between key financial metrics and firm characteristics. The matrix includes correlations between market capitalisation, R&D expenditures, firm size, and leverage. The significance levels are denoted by asterisks, with *** indicating statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

		1	*2*	*3*	*4*
1	*MARKETCAP*	1.00			
2	*R&D*	0.509^{***}	1.00		
3	*SIZE*	-0.366^{***}	-0.110^{***}	1.00	
4	*LEV*	-0.219^{***}	-0.192^{***}	0.055^{*}	1.00

*Note: *p<0.10, **p<0.05, ***p<0.01*

Table 11. Correlation matrix including R&D expenditures

Market capitalisation exhibits a strong, statistically significant positive correlation with R&D (r = 0.509). This suggests that firms with higher market capitalisation tend to invest more in R&D relative to their revenue. This positive relationship indicates that the market values firms' investments in innovation and research, likely due to the potential long-term growth and competitive advantages these investments can bring. Conversely, market capitalisation has a significant negative correlation with firm size (r = -0.366). This suggests that larger firms, when measured by assets, tend to have lower market capitalisation when deflated by revenue. This could mean that smaller firms are often perceived as having higher growth potential, which is reflected in their higher market valuation relative to their size. Smaller firms may be more capable of rapid innovation, leading to higher investor confidence and market value. Additionally, Leverage exhibits a significant negative correlation with market capitalisation (r = -0.219), suggesting that firms with higher leverage tend to have lower market capitalisation. This could indicate that high levels of debt are viewed negatively by investors, possibly due to the increased financial risk associated with higher leverage, leading to a lower market valuation.

R&D shows a significant weak negative correlation with firm size (r = -0.110), indicating that firms investing a higher proportion in R&D tend to be smaller in terms of assets. This could be because smaller firms may rely more heavily on innovation to compete with larger firms, thus allocating a higher proportion of their resources to R&D activities. Additionally, Leverage has a significant negative correlation with R&D (r = -0.192), suggesting that firms with higher leverage tend to invest less in R&D. This relationship might be due to the financial constraints imposed by high debt levels, limiting the firm's ability to allocate resources to innovation and research activities.

Lastly, Leverage shows a very weak positive correlation with firm size (r = 0.055), which is statistically significant at the 5% level. This indicates that larger firms tend to have slightly higher leverage. Larger firms may have more established credit histories and access to capital markets, allowing them to take on more debt relative to smaller firms.

5.1.2 Regression results

The regression results of the first part of the study are shown in Table 12. The regression analysis explores the immediate and lagged effects of R&D investments on market capitalisation using both OLS and FE models.

	MARKETCAP	
	OLS	*FE*
R&D	0.772^{***}	0.423^{***}
	(0.088)	(0.085)
$R\&D^2$	0.141^{***}	0.051^{***}
	(0.026)	(0.022)
$R\&D_{t-1}$	0.0005	-0.004
	(0.034)	(0.011)
$R\&D_{t-3}$	-0.014	-0.022^{***}
	(0.022)	(0.007)
SIZE	-0.253^{***}	-0.606^{***}
	(0.015)	(0.023)
LEV	-0.065^{***}	0.010
	(0.017)	(0.011)
Year FE?	No	Yes
Firm FE?	No	Yes
Observations	1,895	1,895
R^2	0.411	0.969
Adjusted R^2	0.406	0.965
Residual Std. Error	0.359 (df = 1880)	0.087 (df = 1674)
F Statistic	93.537^{***} (df = 14; 1880)	
		*Note: *p<0.10, **p<0.05, ***p<0.01*

Table 12. Regression results R&D expenditures

Table 12 shows that R&D expenditures significantly positively impact market capitalisation in both the OLS and FE models, with the effect being stronger in the OLS model ($\beta = 0.772$, $p < 0.01$) than in the FE model ($\beta = 0.423$, $p < 0.01$). This indicates that when companies invest in R&D, it has a positive effect on the market value. Investing in innovation and new technologies is seen as an important driver of value by investors.

When looking at the lagged R&D terms, which show the delayed effect of R&D expenditures on market value, the medium-term (one-year lag) does not show a significant effect, both for the OLS model and the FE model. This indicates that when a company invests in R&D, after one-year the effect on the market capitalisation is not significant. Investors do not value such investment in innovation positively or negatively after one year. However, after three years (long-term effect), when taking into account the fixed effects, there is a negative significant effect of R&D investments on the market capitalisation in the FE model. This means that the initial positive reaction to R&D investments diminishes over time. After three years, these investments might even be perceived negatively by investors. This could be due to several factors, like including the realisation of high costs, delayed returns, or potential failures in the commercialisation of R&D projects.

Firm size (SIZE) shows a significant negative effect on market capitalisation, for both models. As described in Section 5.1.1, smaller companies receive higher market values from investors compared to larger firms. This is probably due to the growth potential of smaller firms, while bigger firms are often in a more mature stage of growth. Leverage (LEV) shows a significant negative impact on market capitalisation in the OLS model ($\beta = -0.065$, $p < 0.01$) but is not significant in the FE model ($\beta = 0.010$). This indicates that higher leverage (more dent relative to equity) negatively affects market value when not accounting for firm-specific effects. This means that investors generally prefer equity over debt when valuing a company, which is not unexpected.

The squared term of R&D intensity ($R\&D^2$) shows a significant positive effect on market capitalisation in both models. This suggests that higher levels of R&D investment have increasingly positive effects on market value, which highlights the non-linear relationship between R&D and market capitalisation. This could be because larger R&D budgets allow for more ambitious projects, better technology, or more innovation, which are highly valued by the market.

Regarding the overall model performance, the R-squared (R^2) values indicate that the FE model explains a much larger proportion of the variance in market capitalisation (R2 = 0.969) compared to the OLS model (R2 = 0.411). Therefore, including the FE model seems like a valuable choice, as this model suggests that it is more effective in capturing the effects of R&D investments on the market value.

All in all, the regression results demonstrate that R&D investments have a significant positive impact on market capitalisation in the short-term, underscoring the importance of innovation in driving market value. However, the medium-term effects are not significant, indicating that the benefits of R&D investments do not persist over time. The long-term analysis shows a negative impact when considering the FE model, suggesting that the initial optimism surrounding R&D investments may decrease due to high costs, delayed returns, or unsuccessful commercialisation. It can relate to overenthusiasm of investors, who first perceive R&D investments as good news, but later this seems too optimistic. Additionally, the lack of significant medium-effects and the negative long-term effects might be influenced by other factors or noise, such as market volatility or changes in investor sentiment, which can make it harder to see the lasting impact of R&D investments on market value.

5.2 MEDIA ATTENTION

This section presents the results of the analysis focusing on the impact of media attention on firm market value. The analysis begins with the correlation matrix, which is examined to understand the relationships between variables, particularly the link between media attention and market value. The results of the regression analysis are then detailed, revealing the effect of AI-related media coverage on market capitalisation.

5.2.1 Correlation matrix

Table 13 presents the correlation matrix, which provides insight into the relationships between key financial metrics and firm characteristics. The matrix includes correlations between media attention, market capitalisation, R&D expenditures, firm size, and leverage. The significance levels are denoted by asterisks, with *** indicating statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

		1	*2*	*3*	*4*	*5*
1	*MARKETCAP*	1.00				
2	*MEDATT*	0.340***	1.00			
3	*R&D*	0.541***	0.511***	1.00		
4	*SIZE*	-0.297***	-0.011	-0.100*	1.00	
5	*LEV*	-0.199***	-0.136**	-0.242***	-0.137**	1.00

*Note: *p<0.10, **p<0.05, ***p<0.01*

Table 13. Correlation matrix including media attention

Market capitalisation shows a statistically significant positive correlation with R&D expenditures (r = 0.541, $p < 0.01$), similar to the strong positive correlation found in the first correlation matrix (r = 0.509). This consistency suggests that firms with higher market values tend to invest more in R&D, or firms with high R&D expenditures experience higher market values. This strong relationship underscores the link between a firm's market presence and its commitment to innovation.

Market capitalisation also has a significant positive correlation with media attention (r = 0.340, $p < 0.01$), suggesting that firms with higher market value tend to receive more media coverage, both deflated by revenue and thereby normalised for company size. Companies with higher market capitalisation relative to their revenue tend to be more visible, attracting more media attention. This could be because higher market value often signifies better performance, leadership in the industry, or other attributes that make a company newsworthy. However, market capitalisation has a significant negative correlation with firm size (r = -0.297, $p < 0.01$), similar to the negative correlation observed in the first correlation matrix (r = -0.366). This suggests that while more revenue is generated, the market value does not increase proportionately. Investors might perceive smaller firms as having higher growth potential relative to their size, thus assigning them higher market valuations. Additionally, it negatively correlates with leverage (r = -0.199, $p < 0.01$), indicating that firms with higher leverage tend to have lower market capitalisation. This similarity to the first correlation matrix (r = -0.219) implies that high leverage is viewed unfavourably by investors, possibly due to the increased financial risk associated with higher debt levels.

Media attention shows a moderate positive correlation with R&D expenditures (r = 0.511, $p < 0.01$), implying that companies investing more in R&D gain more media coverage regarding AI, highlighting the media's focus on innovation. This shows that investing in innovation by doing R&D expenditures leads to higher media attention regarding AI-related news announcements. Media attention has no significant correlation with firm size, confirming that media attention is not significantly influenced by the size of the firm, which is the case because media attention is deflated by firm size. However, media attention has a slight negative correlation with leverage (r = -0.136, $p < 0.05$), indicating that firms with higher media attention might adopt more conservative financial strategies, maybe to maintain a favourable public image and investor confidence.

R&D expenditures exhibit a weak significant negative correlation with firm size (r = -0.100, $p < 0.10$), consistent with the first correlation matrix (r = -0.110). This suggests that as the size of the firm increases, its expenditures on R&D tend to decrease slightly. This could indicate that larger firms may rely on established products and processes rather than investing heavily in new R&D. Additionally, R&D shows a significant negative correlation with leverage (r = -0.242, $p < 0.01$), similar to the first correlation matrix (r = -0.192), indicating that firms with higher R&D investments tend to have lower leverage. This suggests that firms focusing on innovation prefer to maintain lower debt levels to avoid financial constraints that could hinder their R&D activities.

5.2.2 Regression results

The regression results of the second part of the study are shown in Table 14. The regression analysis explores the effect of media attention on market capitalisation using both OLS and FE models.

	MARKETCAP	
	OLS	*FE*
MEDATT	0.073^{**}	0.083^{***}
	(0.030)	(0.019)
R&D	0.604^{***}	0.635^{***}
	(0.202)	(0.138)
R&D^2	0.069	0.133^{***}
	(0.061)	(0.046)
SIZE	-0.294^{***}	-0.646^{***}
	(0.039)	(0.050)
LEV	-0.106^{***}	0.022
	(0.035)	(0.018)
Year FE?	No	Yes
Firm FE?	No	Yes
Observations	449	449
R^2	0.446	0.981
Adjusted R^2	0.432	0.978
Residual Std. Error	0.394 (df = 437)	0.078 (df = 385)
F Statistic	31.969^{***} (df = 11; 437)	
		*Note: *p<0.10, **p<0.05, ***p<0.01*

Table 14. Regression results media attention

Table 14 highlights the effect of AI-related media coverage on market capitalisation. In both the OLS and FE models, increased AI-related media attention is associated with an increase in market capitalisation. In the OLS model, the effect is significant at the 5% level and in the FE model the effect is significant at the 1% level. Also, the effect is slightly stronger in the FE model (β = 0.083) compared to the OLS model (β = 0.073) .

The positive impact of AI-related media coverage on market value suggests that more media attention enhances market value, likely due to increased visibility and investor interest in AI initiatives. Increased media coverage about a firm's AI initiatives raises awareness among investors. This increased visibility can attract more attention from potential investors who are interested in AI and its potential for growth and innovation. Next to that, frequent mentions in the media about AI can signal to investors that the firm is at the forefront of technological advancements. This perception can lead to greater investor confidence and a belief in the firm's potential for future growth and profitability.

In this sample of 50 firms, R&D expenditures positively and significantly impact market capitalisation in both the OLS and FE models. The effect is slightly weaker in the OLS model than in the first part (β = 0.604 compared to β = 0.772), but it is still significant at the 1% level. However, in the FE model, the results show an even stronger effect (β = 0.653 compared to β = 0.423). This underscores that investment in R&D is a strong driver of market value across different samples of firms. The consistency between the first sample (S&P 500) and this selection of 50 firms shows that the selection taken is a good representation of the S&P 500 index.

Additionally, the consistent findings regarding SIZE (β = -0.294*** and β = -0.253***) and LEV (β = -0.106*** and β = -0.065***) indicate that the selection of 50 firms is a good representation of the 500 firms in the first sample. The selection accurately reflects the key relationships and trends observed in the larger sample, indicating that it is likely a representative subset.

The overall model performance, indicated by R-squared (R^2), suggests that approximately 44.6% (R^2 = 0.446) of the variance in market capitalisation can be explained by the independent variables included in the model. The R^2 value for the FE model is significantly higher at 0.981, indicating that 98.1% of the variance in market capitalization is accounted for by the model when controlling for firm-specific and time-specific effects. The higher R^2 value in the FE model suggests that it provides a better fit for the data. This improved model fit highlights the importance of accounting for unobserved heterogeneity and firm-specific characteristics when analysing the impact of R&D expenditures and media attention on market value.

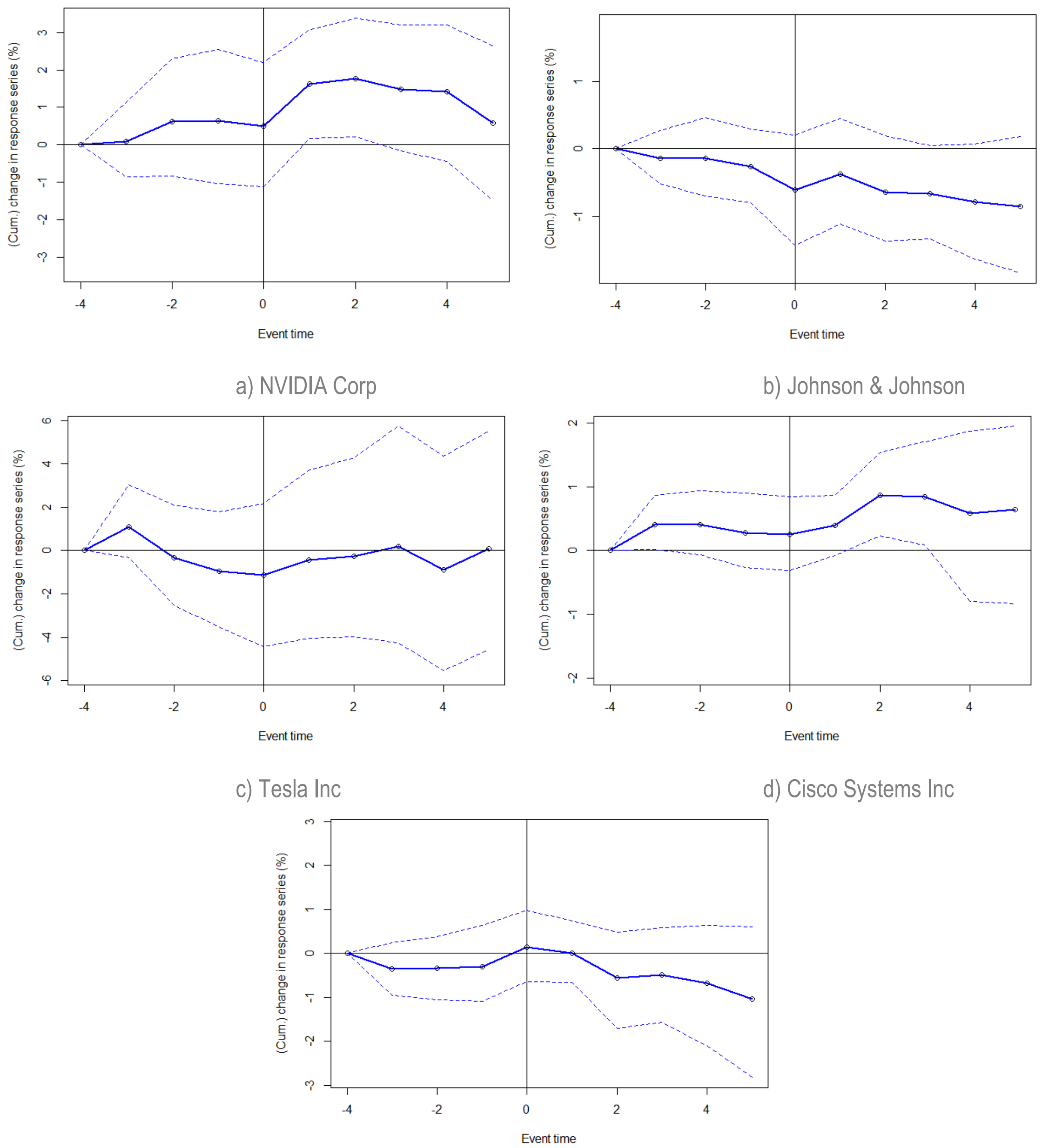
In summary, the regression results illustrate the significant positive impact of AI-related media attention and R&D expenditures on market capitalisation. The findings highlight that increased media coverage enhances market value by attracting investor interest and signalling the firm's commitment to technological advancements. Additionally, R&D investments remain a robust driver of market value, reinforcing the importance of innovation in maintaining competitive advantage. The consistency of these results across different samples underscores the reliability of the study's findings. Also, the model fit, as evidenced by the high R-squared value in the FE model, underscores the effectiveness of including the FE model in capturing the impact of media attention on market value.

5.3 MARKET RESPONSE TO NEWS

This section provides a descriptive analysis of the results from the event study, starting with the market's reaction to AI-related announcements for each individual company. The plots presented illustrate the CARs over the five day event window, showing five days before (including day 0), and five days after the announcement. The blue line represents the CAR, capturing the impact of the announcements on the stock prices. The dashed lines indicate the confidence intervals (95% confidence), providing a measure of variability and uncertainty in the market's reaction. After evaluation of the results of the individual companies, the results of the total sample are discussed and interpreted.

5.3.1 Event study per company

First of all, the results per company are plotted in Figure 10. This includes 22 events (AI announcements) per company.



a) NVIDIA Corp

b) Johnson & Johnson

c) Tesla Inc

d) Cisco Systems Inc

e) Amazon.com Inc

Figure 10. Event study results for all five companies separately

NVIDIA Corp (Figure 10a)

The plot shows an initial upward trend in the CAR before the event day, with a slight decrease just before the announcement. Generally, this indicates positive anticipation leading up to the event. On the event day (day 0), there is a significant increase in the CAR, suggesting a positive reaction from the market. This initial positive sentiment continues, peaking on day +2. However, after this peak, the CAR declines, stabilising near the initial levels by day +5.

The widening confidence intervals post-event indicate increased variability and uncertainty in the market's reaction, suggesting that the observed changes may not be statistically significant over the entire period. Overall, the market initially reacts positively to NVIDIA's AI announcements. The positive CAR and confidence intervals after the announcements suggest that investors have a favourable sentiment toward NVIDIA's AI initiatives. As noted earlier, after three days, external noise and other market factors increasingly influence the data, making it harder to isolate the impact of the AI announcements.

Johnson & Johnson (Figure 10b)

The plot shows a slight downward trend in the CAR before the event, indicating negative sentiment or uncertainty leading up to the announcement. On the event day, there is an increase, suggesting a slight positive reaction from the market. However, this positive reaction is short-lived as the CAR quickly declines, continuing a downward trend over the subsequent days, stabilising at a lower level by day +4.

The widening confidence intervals post-event reflect increased variability and uncertainty in the market's reaction, with the intervals frequently overlapping zero. After the first day (+1), the subsequent decline and variability imply that the market's confidence of the AI announcements is limited. But, it seems that investors react positively on the event day on an AI announcement made by Johnson & Johnson.

Tesla Inc (Figure 10c)

The plot shows a trend where the CAR initially is positive four days before the event but then declines, indicating negative sentiment or uncertainty leading up to the announcement. On the event day, there is a slight increase in CAR, suggesting a modest positive reaction from the market. This increase continues until day +2, after which the CAR declines. From day +3 to day +4, the CAR stabilises and shows a slight increase by day +5.

The widening confidence intervals post-event indicate increased variability and uncertainty in the market's reaction. Therefore, the market reaction to Tesla's AI announcements shows initial negative sentiment leading up to the event, a modest positive reaction on the announcement day, and fluctuating sentiment afterward. The increased variability in the confidence intervals suggest that the market's response to Tesla's AI announcements is mixed. This suggests that investors are cautious and possibly concerned about the implications of AI investments.

Cisco Systems Inc (Figure 10d)

The plot shows a slight upward trend in the CAR before the event, with CARs above zero. On the event day, there is a minor increase in CAR, suggesting a modest positive reaction from the market. This positive sentiment continues in the days following the announcement, with the CAR reaching its peak around day +2. However, after peaking, the CAR declines slightly but remains above zero through the rest of the event window, indicating a sustained but moderated positive impact.

The widening confidence intervals post-event indicate increased variability and uncertainty in the market's reaction, suggesting that while the overall sentiment is positive, there is significant uncertainty about the sustainability of the impact. The market reaction to Cisco's AI announcements shows an initial positive sentiment leading up to and following the event, with the CAR peaking around day +2. The sustained positive CAR indicates a generally favourable market response, but the broad confidence intervals highlight significant uncertainty about the longer-term impact.

Amazon.com (Figure 10e)

The plot shows a relatively flat trend in the CAR before the event, indicating little anticipation or sentiment leading up to the announcement. On the event day (day 0), there is a slight increase in CAR, suggesting a modest positive reaction from the market. However, this positive reaction is short-lived as the CAR peaks on the event day and then begins to decline. By day +1, the CAR starts to decrease, and this downward trend continues throughout the rest of the event window, ultimately stabilising below zero by day +4.

The sustained negative CAR post-event suggests that the initial positive reaction was not strong or sustained. The confidence intervals widen post-event, indicating increased variability and uncertainty in the market's reaction. This implies that while there may has been initial optimism, the initial positive sentiment is overshadowed by subsequent declines, reflecting investor uncertainty or possible reassessment of the announcement's value.

All in all, the event study results demonstrate that AI announcements generally result in a positive short-term reaction from the market, as indicated by the initial spikes in CAR for the companies. However, after a few days the impact remains uncertain, with CARs often stabilising or declining in the days following the event. The confidence intervals in each plot highlight significant variability and uncertainty, suggesting that while the market initially responds positively to AI news, this sentiment is not consistently sustained. This could be due to various factors, including market corrections, the release of additional information, or other external influences.

The most crucial insight is the market's immediate reaction to AI announcements, which tends to be positive. This indicates that investors initially view AI-related news favourably, reflecting optimism about the potential benefits of AI technologies. It highlights the importance of innovation and technological advancement in driving investor sentiment.

5.3.2 Event study all companies

The results of the total sample are shown in Figure 11. The total sample provides insights into the market reactions to AI announcements by aggregating the responses of all five companies. By displaying the companies together, it becomes easier to compare how different firms, from various sectors and with different characteristics, respond to AI announcements. This mitigates individual variability and helps identify common patterns and trends, offering a more generalised view of market sentiment.

As illustrated in Table 10 from Section 4.3.1, the five companies have different characteristics, which is why beyond the individual company level, the total sample can be valuable for investors interested in understanding the wider economic implications of AI technology adoption. Furthermore, the results enhance the statistical power of the analysis, allowing for a more robust determination of the significance of the observed market reactions.

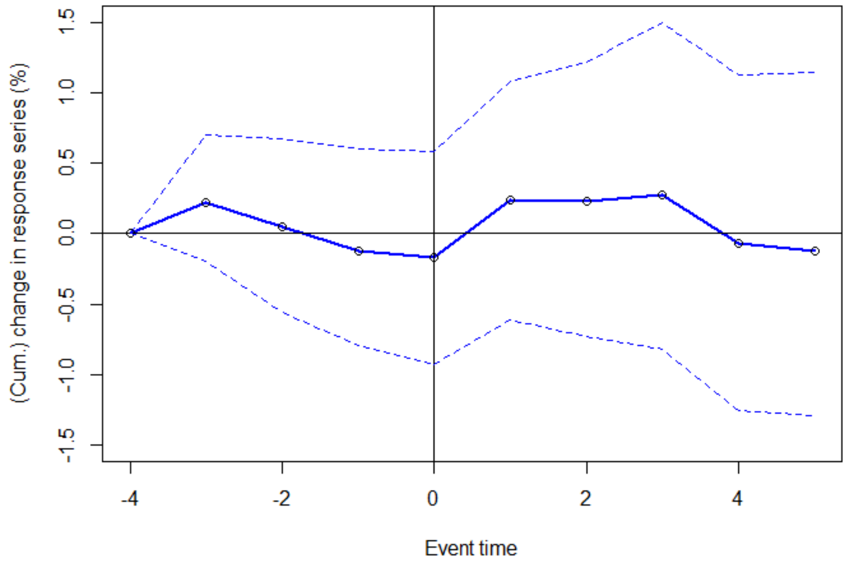


Figure 11. Event study for all five companies

The CARs for all five companies - NVIDIA Corp, Johnson & Johnson, Tesla Inc, Cisco Systems Inc, and Amazon.com Inc - are analysed over a ten-day window, encompassing 110 AI-related news announcements (22 per company; 2 per year from 2013 to 2023).

Analysing the pre-announcement sentiment provides context for understanding the market's reaction to the announcement. If there is positive anticipation leading up to the event, it suggests that investors might have been expecting good news, which could explain a part of a positive reaction. Conversely, if there is negative sentiment or uncertainty before the announcement, the positive reaction might indicate that the news exceeded investor expectations. The CAR shows an initial upward trend from day -4 to -3, indicating positive anticipation. However, this is followed by a decline leading up to the event day, suggesting mixed sentiment or uncertainty among investors. This suggests that the observed market reactions are mostly due to the announcement. In this study, the chosen announcements were first-time announcements, meaning they likely introduced new information to the market.

On the event day (day 0), there is a noticeable increase in CAR, which continues to rise, showing positive returns until about day +3. This positive reaction suggests that the market initially views AI announcements favourably, expecting them to enhance the companies' competitive advantages and future profitability. Given the negative sentiment or uncertainty before the announcement, this positive reaction underscores the favourable investor sentiment regarding AI investments.

However, after day +3, the CAR begins to decline and stabilise, which could indicate that the initial enthusiasm is not sustained. This pattern suggests that while investors initially respond positively to AI announcements, other factors or a reassessment of the announcements' implications may temper this enthusiasm over time. The post-event decline could also be influenced by market noise, making it challenging to discern the effects of the announcements after a few days. This is also confirmed by the widening confidence intervals after the event day, which indicate increased variability and uncertainty in the market's reaction. These intervals also encompass the zero line, meaning that the CAR could be zero within this range, implying that the observed changes might not be statistically significant. This suggests that the market's response could be influenced by random movements or other unrelated factors rather than solely by the AI announcements.

To conclude, the results of the event study demonstrate a consistent positive market reaction to AI announcements, evidenced by the increase in CAR up to day +3. This is also underscored by the negative sentiment before the announcement, suggesting that investors did not expect the announcement. However, after a few days the impact remains uncertain, with the CAR declining and stabilising back to the trend from before the event, reflecting the challenges of isolating the sustained effects of AI announcements amidst market noise. Overall, the impact of an AI announcement is positive, with showing positive abnormal returns for three days after the event.

6. DISCUSSION

The results section shows that this study provides valuable insights into the relationships between AI investments and the market value of publicly traded companies. This section discusses what can and cannot be concluded from the results, reflects on the robustness of the tests conducted and highlights areas for potential improvement.

6.1 R&D INVESTMENTS AND MARKET VALUE

The first hypothesis proposes that firms investing in R&D would witness a positive impact on their market value in the period from 2013 to 2023, both in the short-term and long-term. The results show a significant positive impact of R&D expenditures on market capitalisation in the short-term. Unless some studies highlight the negative aspects or limitations of R&D investments (Ali et al., 2012; Kim et al., 2018; Zhang, 2015), this aligns with existing literature suggesting that R&D investments drive innovation, leading to new products and processes that provide a competitive edge (Cohen & Levinthal, 1990; Samuel et al., 1996; Chan et al., 2002). Accordingly, it shows that investing in innovation is an important driver of market value.

According to the EMH (Fama, 1970), market value reflects all available information, including expectations about future benefits. Therefore, the immediate positive market reaction to R&D announcements can be attributed to investor excitement and speculation about potential breakthroughs. The short-term gains can be linked to initial investor optimism, as the market quickly incorporates the potential future benefits of the R&D investments. However, as time progresses, the market adjusts its expectations based on the actual performance and outcomes of these investments. This adjustment is reflected in the lagged variables, which capture the delayed impact of R&D on market value.

Investors may speculate that the new R&D initiatives will result in innovative products or improvements, leading to higher revenues and competitive advantages. This speculation drives up the stock price in the short-term. However, the long-term effects appear less pronounced, which could be attributed to the inherent risks and uncertainties associated with R&D activities. Investors might initially respond positively to R&D announcements due to expectations of future growth, but sustaining this momentum requires continuous innovation and successful commercialisation of research outputs. If the R&D investment leads to successful innovations, sustained competitive advantages, and increased profitability, the market value may continue to rise, reflecting these long-term benefits.

The inclusion of lagged effects was particularly insightful, which reveals that the medium-term effects are not significant. This indicates that the benefits of R&D investments do not persist over time. The long-term analysis shows a negative impact, suggesting that the initial optimism surrounding R&D investments may decrease due to high costs, delayed returns, or unsuccessful commercialisation. The R&D investments do not lead to significant innovations or the market's initial expectations were overly optimistic. This led to the negative effects regarding the long-term investments in R&D.

The OLS and FE models were instrumental in capturing these dynamics. The FE model, in particular, controlled for unobserved heterogeneity, providing a more nuanced understanding of the relationship between R&D investments and market value. However, the assumption of linearity in the relationship between R&D intensity and market value might not fully capture this relationship. This is confirmed by the positive significant effect of the squared term of R&D, which shows that higher levels of R&D investment have increasingly positive effects on market value. Including this non-linear term helped mitigate this nonlinear relationship, but further exploration with more sophisticated models could yield more reliable insights.

From an investor's perspective, the findings of this study underscore the importance of considering both the immediate and long-term impacts of R&D investments. Investors should recognise that while R&D expenditures can lead to significant short-term market value gains due to initial optimism, these effects may not be sustainable without continuous innovation and successful commercialisation of outputs. Therefore, investors should look for firms with a robust track record of converting R&D investments into marketable products and sustained competitive advantages.

For firms, these findings highlight the critical role of strategic R&D investment in driving market value. Companies should focus not only on the quantity of R&D spending but also on the effectiveness of these investments in generating tangible innovations. Maintaining transparency and regularly updating investors on R&D progress and milestones can help sustain investor confidence over the long-term. Additionally, firms should adopt a balanced approach to R&D investment, carefully managing the inherent risks and uncertainties to maximise both short-term and long-term benefits. This balanced approach not only enhances market value but also strengthens the firm's competitive position and growth potential.

6.2 MEDIA ATTENTION AND MARKET VALUE

The second hypothesis states that firms experiencing more media attention related to AI activities would witness a positive impact on their market value. The results support this hypothesis, demonstrating that media attention significantly shapes investor perceptions and firm market value. The signaling theory (Connelly et al., 2011) was validated, as positive media coverage enhanced investor confidence and market valuation. However, the variability in media effects, consistent with Wang and Ye (2014), indicates that the sentiment and context of the media coverage are crucial determinants of its impact.

According to the EMH (Fama, 1970), market value reflects all available information, including public sentiment shaped by media coverage. Therefore, media attention can significantly influence investor behaviour by providing cues about a firm’s innovation activities and future prospects. Positive media coverage can create a narrative of success and innovation, attracting investors and driving up stock prices. Conversely, negative or neutral coverage can dampen investor enthusiasm, highlighting potential risks and uncertainties. The results indicate a significant positive relationship between media attention and market value, but this relationship's strength and consistency vary across different contexts and companies. This variability underscores the importance of considering the type and context of media coverage. For instance, an announcement about a groundbreaking AI initiative may have a different impact compared to an article discussing minor updates or general AI-related commentary.

While the methodology used to quantify media attention was robust, it mostly relies on the frequency and nature of announcements made. As described in Section 3.2, this method captures a broad spectrum of news articles related to AI and the company, which also includes articles about ongoing discussions on current technologies or existing innovations. However, it does not exclusively focus on news announcements specifically about new investments in AI, which may dilute the specific impact of significant AI investment news.

Additionally, the selection of 50 companies for the analysis provided a robust sample size to gauge the impact of media attention on market value. The comparable results between this part of the study and the first part focusing on R&D investments reinforce the robustness of the findings. Both studies showed similar relationships between the variables under investigation and market value. It indicates that both R&D investments and media attention are critical drivers of market value across a diverse set of companies. Also, this consistency reinforces the validity of the findings and suggests that the observed trends are not isolated incidents but rather reflect broader market behaviours.

From an investor's perspective, these findings highlight the importance of critically evaluating the media coverage of a firm's AI activities. Investors should consider not only the frequency of media attention but also the sentiment and context of the coverage. Positive media coverage can be an indicator of a firm's potential for innovation and future growth, but investors should remain cautious and look for successful outcomes.

For firms, the results emphasise the critical role of strategic media management in enhancing market value. Companies should actively engage with the media to highlight their AI initiatives, ensuring that their innovations and achievements are communicated effectively to the public. Maintaining a consistent and positive media presence can help attract and retain investor interest. Firms should also be transparent about their AI progress and provide regular updates to sustain media interest and investor confidence over the long-term.

6.3 MARKET REACTION TO AI ANNOUNCEMENTS

The third hypothesis focuses on the market reactions to AI-related announcements. The event study methodology confirmed that AI announcements generally lead to positive abnormal returns, particularly within a few days. Unless there are studies which suggest that investors perceive AI investment announcements as negative news for the majority of firms (Lui et al., 2021), these results align with studies showing positive abnormal returns from AI announcements (Huang & Lee, 2023).

Positive market reactions to AI announcements can indicate investor confidence in the strategic direction of the company and the potential value of the AI investment. Conversely, negative reactions may reflect concerns about the feasibility, cost, or potential impact of the AI initiative. According to the EMH, the market value of a firm should reflect all available information, including the expected future benefits of current investments (Fama, 1970). This means that when firms announce AI initiatives, investors incorporate their expectations about the long-term profitability and strategic advantages of these investments into the stock price immediately. Therefore, the immediate market reaction also projects the anticipated long-term benefits of AI initiatives as perceived by investors. Also, the EMH posits that stock prices quickly adjust to new information and then stabilise as the market digests and incorporates the full implications of the event.

Reflecting on the individual event study graphs, it is evident that AI announcements generate diverse market reactions among different firms. These variations suggest that the impact of AI initiatives is not uniform and heavily depends on firm-specific factors such as the company's existing market position, sector dynamics, and the perceived feasibility of the AI projects. For example, companies with a strong track record in innovation may experience more positive investor responses compared to those in sectors where AI adoption is less common or more challenging. This diversity in reactions underscores the complexity of predicting market responses to AI announcements and suggests that investors should carefully consider the context and specifics of each firm's AI strategy. While some companies may benefit from immediate investor optimism, others may face scepticism, highlighting the nuanced nature of market perceptions towards AI initiatives.

Considering the total sample, the event study shows an overall positive trend reflecting general optimism about the potential of AI to drive growth and innovation across various industries. However, the increased variability over time suggests that initial positive reactions are subject to reassessment as more information becomes available. This indicates that while AI announcements can boost market confidence initially, sustaining this positive sentiment requires clear, ongoing communication about the progress and outcomes of AI initiatives. The broad range of responses within the total sample highlights that while the market generally views AI positively, the ultimate impact on firm value can vary significantly depending on execution and tangible results. Therefore, in line with the first part regarding the effect of R&D investments on market value, the long-term effect of AI announcements on market value is dependent on successful implementation and continuous performance updates.

Despite the initial positive reactions, the observed decline and stabilisation of CAR after a few days suggest that the market's enthusiasm may be tempered by other factors. These could include reassessments of the announcement's implications, emerging competitive responses, or other concurrent news that could influence investor sentiment. Additionally, the overlapping confidence intervals with the zero line post-event indicate that these changes might not be statistically significant, implying that the initial reactions could be subject to random market fluctuations or noise. While the immediate positive reaction underscores the market's initial optimism, the variability and stabilisation suggest that as more information becomes available or as initial expectations are reassessed, investors reassess their initial valuation. This pattern underscores the EMH of Fama (1970), showing that stock prices quickly adjust to new information and then stabilise as the market digests and incorporates the full implications of the event.

From an investor's perspective, these findings highlight the importance of timing and due diligence. While AI announcements can lead to immediate gains, investors should be cautious of the potential for volatility and the need for a deeper analysis of the firm's AI strategy and execution capabilities. The initial market reaction can provide opportunities for short-term gains, but sustained value creation requires a thorough understanding of how the AI initiatives will be implemented and their long-term potential. This is also illustrated in the first part of this study, which shows that while R&D expenditures can lead to significant short-term market value gains due to initial optimism, these effects may not be sustainable without continuous innovation and successful commercialisation of outputs.

For firms, the results emphasise the importance of strategic communication and follow-through on AI initiatives. Announcing AI projects can generate positive market reactions, but sustaining investor confidence requires transparency and ongoing updates about the progress and outcomes of these initiatives. Companies should manage expectations by clearly articulating the strategic benefits of their AI investments and providing regular updates to demonstrate tangible progress and mitigate the risk of investor disillusionment.

7. CONCLUSION

The study aimed to answer the research question: “How does the adoption of AI technologies impact the market value of publicly traded companies?” The hypotheses were tested based on the analysis of R&D expenditures, media attention, and market reactions to AI announcements. Through the funnel structure, different samples are chosen for which each round a smaller, interesting sample was taken on the basis of several criteria. This chapter answers the three hypotheses, after which a general conclusion is drawn which answers the research question.

Hypothesis 1: Firms investing in R&D will witness a positive impact on their market value in the period from 2013 to 2023, both in the short-term and long-term.

The findings confirmed a significant positive impact of R&D expenditures on market capitalisation in the short term. This aligns with the literature suggesting that R&D investments drive innovation, leading to new products and processes that provide a competitive edge (Cohen & Levinthal, 1990; Samuel et al., 1996; Chan et al., 2002). According to the Efficient Market Hypothesis (EMH), market value reflects all available information, including expectations about future benefits (Fama, 1970). Therefore, the immediate positive market reaction to R&D announcements can be attributed to investor excitement and speculation about potential breakthroughs.

However, the long-term effects of R&D investments appeared less pronounced. The study revealed that while initial investor optimism drives up stock prices, sustaining this momentum requires continuous innovation and successful commercialisation of research outputs. The inclusion of lagged effects indicated that medium-term benefits do not persist, and long-term analysis showed a negative impact. This suggests that initial optimism may decrease due to high costs, delayed returns, or unsuccessful commercialisation. The positive significant effect of the squared term of R&D investment highlights that higher levels of R&D spending can have increasingly positive effects on market value, but a balanced approach is crucial.

Hypothesis 2: Firms experiencing more media attention related to AI activities will witness a positive impact on their market value in the period from 2013 to 2023.

The analysis of media attention and its impact on market value revealed a positive association. Companies with higher media coverage of their AI activities generally saw a positive market reaction. This aligns with the signaling theory, which posits that media attention can enhance investor perceptions and increase market value. The regression analysis confirmed that media attention, as measured by the number of AI-related news announcements, positively affects market capitalisation. This suggests that media coverage can significantly influence investor sentiment and positively drive market value. However, the variability in media effects indicates that the sentiment and context of the coverage are crucial determinants of its impact.

The EMH suggests that market value reflects all available information, including public sentiment shaped by media coverage. Positive media coverage can create a narrative of success and innovation, attracting investors and driving up stock prices. Conversely, negative or neutral coverage can dampen investor enthusiasm by highlighting potential risks and uncertainties. This variability underscores the importance of considering the type and context of media coverage.

Hypothesis 3: Positive announcements regarding AI activities of firms will correspond with an increase in market value in the period from 2013 to 2023.

The event study methodology confirmed that AI announcements generally lead to positive abnormal returns, particularly within a few days. This aligns with studies showing positive abnormal returns from AI announcements (Huang & Lee, 2023), although some studies suggest that investors perceive AI investment announcements as negative news for the majority of firms (Lui et al., 2021).

Positive market reactions to AI announcements indicate investor confidence in the strategic direction of the company and the potential value of the AI investment. According to the EMH, the market value of a firm should reflect all available information, including the expected future benefits of current investments (Fama, 1970). Therefore, the immediate market reaction also projects the anticipated long-term benefits of AI initiatives as perceived by investors. The EMH posits that stock prices quickly adjust to new information and then stabilise as the market digests and incorporates the full implications of the event.

Reflecting on the individual event study graphs, it is evident that AI announcements generate diverse market reactions among different firms. These variations suggest that the impact of AI initiatives is not uniform and heavily depends on firm-specific factors such as the company's existing market position, sector dynamics, and the perceived feasibility of the AI projects. The variability in the CAR post-event highlights the complexities of isolating the effects of AI announcements after a few days. The confidence intervals indicate significant variability and uncertainty, suggesting that while the market initially responds positively to AI news, this sentiment is not consistently sustained due to market noise and other external factors.

Funnel methodology and research question

By combining these three parts, the study provides a holistic view of the impact of AI investments on market value, addressing the complexities and nuances involved. The funnel methodology, which starts broad with R&D investments, narrows to media attention on AI, and finally focuses on specific market reactions to AI announcements, offers a comprehensive and systematic approach to understanding the financial implications of AI investments.

Investing in AI can provide significant strategic advantages, including enhanced innovation, improved operational efficiency, and a stronger competitive position. The findings of this study underscore that while AI investments can initially boost market value and investor confidence, their long-term success depends on effective implementation, continuous innovation, and strategic communication. Firms should invest in AI to drive growth and maintain a competitive edge in a rapidly evolving technological landscape. However, the variability in market reactions indicates that successful AI investments require careful planning, transparent communication, and ongoing performance updates to sustain investor confidence and realise long-term benefits.

In conclusion, this study has provided valuable insights into the impact of R&D investments, media attention, and AI-related announcements on market value. The findings underscore the critical role of strategic investment, effective communication, and continuous innovation in driving market value and sustaining investor confidence. By understanding these dynamics, both investors and firms can better navigate the complexities of AI investments and capitalise on the opportunities they present.

7.1 LIMITATIONS & RECOMMENDATIONS

This section covers several limitations that should be considered when interpreting the results. It also provides recommendations for future research and practical considerations to enhance the understanding and application of the findings.

First, the regression models used in this study assume a linear relationship between variables. This assumption may not fully capture the potentially non-linear relationships between R&D investments, media attention, and market value. Future studies could explore alternative models that do not rely on this assumption, like nonlinear regression models, thereby offering a more accurate effect of the relationships involved.

Second, the method of measuring media attention through the number of AI-related news announcements does not account for the sentiment or context of the media coverage. The sentiment conveyed in the media can significantly influence investor perceptions, and merely counting the number of announcements may overlook these nuances. Future research could incorporate sentiment analysis to differentiate between positive, neutral, and negative media coverage, providing a more nuanced understanding of how different tones and contexts influence market reactions. Positive sentiment in media articles could reinforce investor confidence and drive market value, while negative sentiment could mitigate the positive effects or even lead to adverse market reactions. Additionally, the study's approach to media attention could be improved by adopting a more detailed categorisation. By distinguishing between types of AI-related news researchers can better isolate the effects of each category on market value. Types of AI-related news could be new AI initiatives, advancements in existing AI technologies, or partnerships and collaborations. This aligns with the findings of Dang et al. (2020), who emphasise the importance of the nature and context of media coverage in shaping investor perceptions.

Third, the study's focus on short-term market reactions to AI announcements, as evidenced by the event study, also presents a limitation. While short-term reactions provide valuable insights into immediate market sentiments, they may not capture the long-term impact of AI investments on firm value. Future research could benefit from a more longitudinal analysis to better understand the sustained impact of AI announcements. This would involve examining the effects over a longer time horizon, revealing more about the lasting effects of AI investments on firm value.

Fourth, the sample size and diversity of the firms analysed could be improved. Although the second part of the study included 50 companies, a larger and more diverse sample could provide a broader perspective and more generalisable results. Expanding the sample to include firms from different industries and regions could help in understanding the varying impacts of AI investments across different contexts. Also for the first part regarding R&D investments, another index, or firms from other countries could be chosen to help understanding the impacts of AI investments across different countries.

7.1.1 The funnel methodology

The funnel approach allows for a broad examination of R&D investments before narrowing down to the specific aspects media attention and AI announcements. This ensures that the analysis captures a wide range of factors influencing market value, providing a holistic view of the impact of innovation and public perception on investor behaviour. By examining the broader context of R&D investments first, the study sets a foundation for understanding how media attention and specific AI announcements fit into the larger picture of a firm's innovation strategy. This layered approach helps to identify both general trends and specific nuances, offering richer insights into the complex dynamics at play.

Using multiple stages enhances the accuracy and reliability of the findings. Cross-checking through different data sources and analytical methods helps to confirm results, reducing the likelihood of biases and ensuring more robust conclusions. By progressively narrowing the focus, the study can isolate the specific effects of AI announcements from other factors influencing market value, such as general innovation activities and media coverage.

For investors, the funnel methodology provides a detailed roadmap for evaluating firms. Starting with a broad assessment of R&D activities helps investors identify companies with strong innovation potential. The subsequent focus on media attention and AI announcements offers specific indicators of how well firms manage public perception and communicate their strategic initiatives.

Future research can build on this approach to examine the long-term impacts of R&D investments, media attention, and AI announcements, providing deeper insights into the sustained effects on market value. The methodology is adaptable to other contexts and countries. While this study focused on AI investments, the same approach can be applied to other technological innovations or strategic initiatives, making it a versatile tool for academic and practical research.

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