The Dynamic Impact of Artificial Intelligence Investment on Firm Performance and Market Value

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Master Thesis

RSM 2025 | MSc Business Information Management

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Date of submission: 19th June 2025

Preface

Acknowledgement

I am sincerely thankful for the support from my thesis supervisor, Dr. Yagmur Ozdemir, for her valuable supports since the beginning of this thesis journey. Her expertise and guidance have shaped the direction and quality of this paper.

I also want to thank my co-reader, Dr. Wei Wang, for providing different perspectives, which help me clarify the missing points in my thesis.

Lastly, I am grateful to my family and friends for their continuous support and encouragement throughout my study Their belief in me is the greatest motivation.

This thesis marks the end of my two-year study at Rotterdam School of Management, Erasmus University Rotterdam, but not the end of my learning journey. I hope this research contributes to the field of AI investment strategies and motivates further exploration in the dynamic effects of emerging technologies.

Executive Summary

Artificial Intelligence investment is considered one of the important business decisions due to its rapid development in recent years. On the one hand, firms' leaders and managers are willing to invest in AI to gain competitive advantages in the short term and to strengthen business innovations as well as internal resources in the long term. On the other hand, firms are under pressures to meet the short-term expectations from investors and stakeholders. Without clear evidence of how firms are impacted after investing in AI over time, firms are struggling to prove their efforts before implementing AI as the investment processes involve costs and resources. This leads us to a critical question: How do the impacts of AI investment differ in terms of short and long term?

This study analyses research papers focusing on the relationship of AI and firm-level outcomes to identify theoretical gaps of prior studies. During the literature review, we find that there are two main streams of research when studying firm-level outcomes. The first one is AI investments improve firm financial performance by offering AI-enabled capabilities, thereby enhancing firms' internal resources and capacities. Whilst the second stream concentrates on the mixed results of firm market valuation after their AI investment- related announcements. Although previous studies do not analyse the dynamic effects of AI investment, their empirical findings suggest short-term negative impacts and long-term positive impacts.

To verify our hypotheses, we examine 61 publicly listed U.S. firms from the S&P Kensho AI Enablers & Adopters Index that invested in AI from 2013 to 2023. Our study employs staggered difference-in-difference research design with relative time indicator and multi-treatment framework to investigate how the effects change year by year after investment. The dependent variables are firm performance, proxied by returns on equity and returns of assets, and firm market value, proxied by Tobin's Q. Whereas the independent variable is AI investment, which requires additional procedures to identified through their AI investment-related statements in annual filings. Hence, we follow an approach using a large language model to scrape and analyse AI investment-related text from the filings retrieved from the U.S. State and Exchange Commission. After confirming firms' engagement in AI investment, we compare AI-investing firms to non-AI firms, which randomly derived from the S&P 500 Index.

Our results show two distinct directions with prior research. One contrary direction shows that AI investments positively impact firm performance and market value in the short term. Whilst the aligned direction shows the positive effects in firm performance and market value in the long term after investing in AI. Furthermore, we find that the effects are strongest at the second and third year after the AI investment year. We employ several robustness checks including winsorisation, alternative estimators and optimal full matching to address our concerns regarding outliers and biases.

The empirical findings from our study extend current literature by using staggered difference-in-difference to analyse the dynamic effects of AI investment on firm performance and market value. Such valuable insights allow researchers to draw causal inferences on the relationship of AI investment and firms, shedding lights for future research on the moderation and mediation relationships of other factors. In addition, the findings provide investors with a detailed roadmap for AI-investing firms evaluation. Whereas for firms' owners and managers, our study serves as evidence for proving long-term values of AI investment.

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Table of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
BV	Book Value
CIK	Central Index Key
DID	Difference-in-Difference
EDGAR	Electronic Data Gathering, Analysis, and Retrieval
IT	Information Technology
LLM	Large Language Model
MV	Market Value
ROE	Return on Equity
ROA	Return on Assets
SEC	Securities and Exchange Commission
TWFE	Two-way Fixed Effects
WRDS	Wharton Research Data Services

1. Introduction

In recent years, firms from various sectors have increasingly invested in AI with a belief that AI brings positive impacts to the way firms do business due to its rapid evolution (Burgess, 2017; Shareef et al., 2021). For instance, the adoption of AI in pharmaceutical businesses improves accuracy, thereby enhancing their operational efficiency (Chetthamrongchai & JERMSITTIPARSERT, 2020). AI integration transforms internal business processes, including damage detection and construction document processing in the construction industry, as well as product recommendations and supply chain management in the e-commerce sector (Pan & Zhang, 2021; Bawack et al., 2022). In the banking and financial services sector, AI-driven solutions can help identify suspicious transactions and automate loan approvals (Ostmann & Dorobantu, 2021; Rahman et al., 2023).

As this emerging technology dominates discussions, an increasing number of firms have invested in AI to gain competitive advantage. According to a survey conducted by Statista (2024), global expenditure on AI-centric systems across all industries was estimated to reach $154 billion in 2023. In addition, according to a survey conducted by McKinsey in 2024, the AI adoption rate among firms has increased dramatically, with more than two-thirds of respondents from different regions reporting that their firms are actively using AI (Singla et al., 2024). These statistics highlight business leaders view AI investment as essential for firms' growth and competitiveness. Indeed, firms across different industries have been investing in AI as a strategic plan, from finance, logistics, retail, e-commerce, and marketing to manufacturing, healthcare, pharmaceuticals, and energy.

Despite its promising potential, the dynamic impacts of AI technologies remain underexplored. The existing literature presents mixed evidence on their empirical magnitude and direction. Several studies provide empirical evidence that AI brings positive value to businesses by transforming their competitive advantages and improving their financial performance (Cheng et al., 2025; Kim et al., 2022; Mishra et al., 2022; Sulivan & Wambal, 2024; Sun & Jiao, 2024; Wamba-Taguimdje et al., 2020). Furthermore, AI investment does not only affect firms' internal performance but also impact firms' external market value. AI-investing disclosures positively influence the investors' expectation, causing firm market value to rise (Dong et al., 2025; Huang & Lin, 2025; Lui et al., 2022; Mishra et al., 2022).

However, these studies do not highlight when and how long the positive effects begin to be realised. On the contrary, there are empirical findings suggesting that AI may negatively impact firms in the short term (Doshi et al., 2021; Lui et al., 2022). While many firms' AI investment efforts are either undisclosed or not publicly reported (Burgess, 2017, p.2), other firms may strategically mention AI-engaged activities in their annual reports to shape stakeholders' perceptions (Yuthas & Dillard, 2002). This poses a significant challenge for researchers and executives seeking to understand the dynamic effects of AI's financial implications. As a result, many firms remain hesitant and reluctant to invest in AI.

One of the most significant challenges for firms' owners, managers, and stakeholders when making decisions regarding AI investments is the gap between short-termism and long-termism. Investors, both institutional and activist, tend to favour short-term profits and neglect the long-term value creation (Fusso, 2012). However, like other technological investments, it may take some time for the gains to be realised (Khallaf et al., 2017). This pressure may lead firms' owners and managers to make trade-off decisions, sacrificing long-term benefits to achieve short-term returns (Tang & Greenwald, 2016).

Therefore, this thesis aims to address critical knowledge gaps in the field of AI investment by concentrating on the impact of AI, which remains unclear due to the prior research's focus on static, aggregate effects. Prior studies employ surveys and case study approaches, which may not fully capture the actual effect of AI implementation. In addition, there is limited understanding of the differences in short-term versus long-term impact of AI investment on firms. While prior research has explored AI's potential benefits, it does not account for how these effects of AI technology implementation change throughout the years. The impacts of AI investments may not be immediately realised, as they may gradually evolve.

To address this gap, our study employs staggered difference-in-difference (DID) analysis with a multi-treatment and relative time framework. We aim to study the causal relationship between AI investment and firm outcomes, particularly firm financial performance and market value. This approach allows us to capture both immediate and long-term effects of AI investment.

Furthermore, it strengthens the causal interpretation by comparing firms in the treatment group to those in suitable control groups over time within a staggered DID framework. This paper analyses firms in the U.S. market from 2013 to 2023, using text extraction and textual analysis of firm-level annual filings to capture firms' AI investment disclosures. The primary objective of this paper is to contribute empirical results and theoretical insights to the current literature. Furthermore, it aims to support managers, stakeholders, and investors in making more informed decisions. Through this work, the thesis aims to deepen the scholarly and practical understanding of AI's economic value and strategic potential. To this end, the thesis addresses the following research questions:

(1) When does AI investment pay off?

(2) Do the short-term effects of AI investment on firms differ from its long-term effects?

2. Literature Review & Theoretical Foundation

In this chapter, we conduct a literature review to establish the theoretical foundation for the main concepts of our study. We select Google Scholar and Scopus as the primary databases for this process due to their broad coverage of academic literature (Martín-Martín et al., 2021). The literature search is conducted using the following query:

“AI” **OR** “artificial” **AND** “intelligence” **AND** “firm” **AND** “impacts”

In addition, we define two criteria for screening and selecting studies. First, the papers must be peer-reviewed and second, the papers must be written in English. A summary of relevant literature review is shown in *Appendix A*.

2.1. The State of AI Investment

The first formal foundation of AI was established by Alan Turing in the 1940s when he raised a question of whether machine could think (Muthukrishnan et al., 2020; Turing, 2009). Since then, the definition of AI has evolved with its explanation differs across fields depending on the contexts and purposes. Hence, it is difficult to explain AI in a precise way while ensuring its definition is applicable in multiple contexts. Within the scope of this paper, we adopt the general concept of AI as an artificial system that can learn, repeat, create and interpret tasks similarly to humans (Haenlein & Kaplan, 2019; Masnikosa, 1998).

In recent years, an increasing number of firms have invested in AI to exploit its value for their purposes, driven by its rapid development and applications over the past decade (Lee et al., 2022). With the capabilities that resemble humans, AI can transform a firm’s competitive advantage (Chen et al., 2023; Kassa et al., 2025; Sharma & Kuma, 2024). The technology is perceived as a strategic tool as it introduces new perspectives to innovation and management (Chen et al., 2023; Kassa et al., 2025).

When firms integrate AI successfully, its application can increase their productivity and retention rate (Wang & Siau, 2019). Indeed, when firms perceive AI-driven solutions as a complementary tool, their internal resources, such as workforce skills, management practices, and innovation capacity can be improved (Argyres & Zenger, 2012). This view aligns with the Resource-Based

View theory, which was introduced by Barney (1991). The theory implies that when firms manage to exploit values from the technology adoption, these values can improve their internal resources and capabilities. Since internal resources and capabilities include skilled workforce, working culture, management style and the abilities to adopt new technology, which may be impossible for other firms to imitate, they become firms' competitive advantage in the long term (Barney, 1991).

When AI is integrated as a complementary tool within an organisation, it can function as a strategic asset, enabling the creation of unique resource combinations that are difficult for competitors to replicate (Argyres & Zenger, 2012). A survey by McKinsey found that 40 percent of business leaders reported that their organisations plan to increase AI investment (Chui et al., 2023). Additionally, in the year 2023, approximately 57 percent of top-performing organisations have either adopted AI or plan to do so within the next year, while less than half of mainstream firms have the same vision (Njeru, 2023).

These results highlight the widespread recognition of AI investment as a promising and essential technology for organisational growth and competitiveness. Reflecting this perception, AI integration extends across various industries, including finance, logistics, retail, e-commerce, marketing, manufacturing, and vital sectors such as healthcare, pharmaceuticals, and energy.

AI is divided into two groups based on its functionalities and capabilities (Tai, 2020; Wang & Siau, 2019). The first group is weak AI. Weak AI is designed to excel in specific tasks, for instance, autonomous driving and facial recognition (Tai, 2020). The second classification is strong AI, which can process multiple tasks efficiently like a human, including self-awareness abilities (Tai, 2020). Current AI is primarily weak AI since its applications depend on training data and programming algorithms (Wang & Siau, 2019). However, in this study, we concentrate on the strategic decision to invest in AI rather than the technical aspects of how AI systems operate.

AI investment strategies are different depending on the sector. In finance, for example, firms employ AI to enhance credit risk management, as its ability to process large datasets improves both lending decisions and fraud detection (Königstorfer & Thalmann, 2020; Maple et al., 2023). In logistics, AI-driven applications are mainly used for route optimization; predictive analytics enable companies to optimize delivery times and reduce operational costs through real-time traffic analysis (Njeru, 2023; Wamba-Taguimdje et al., 2020).

Retail and e-commerce businesses integrate AI into internal processes such as sales forecasting, personalised marketing, and inventory management to create better customer experiences (Wamba-Taguimdje et al., 2020). AI also enhances creativity in marketing by enabling targeted advertising and more effective customer segmentation, allowing marketers to generate valuable insights from data (Keegan et al., 2022; Mishra et al., 2022). In manufacturing, AI supports predictive maintenance and quality control, which helps firms prevent equipment downtime (Wamba-Taguimdje et al., 2020).

Within the healthcare sector, AI is typically applied to disease diagnosis and personalized patient care, thereby improving both treatment accuracy and patient health outcomes (Lee et al., 2022). In the energy sector, firms use AI to increase grid efficiency and reduce excessive energy consumption (Wamba-Taguimdje et al., 2020).

Although the enthusiasm over AI is obvious, the current literature shows mixed perspectives on its impacts at firm-level outcomes. Several studies highlight the negative impacts of AI investment on firms (Lui et al., 2022; Song et al., 2025). Implementing AI incurs additional costs related to infrastructure upgrades, energy consumption, workforce training, and compliance challenges (Lui et al., 2022), and hidden costs such as the cost of data transfer latency (Doshi et al., 2021). These financial burdens can outweigh the anticipated benefits and bring adverse effects.

Due to these uncertainties, managerial attitudes toward AI adoption remain mixed (Cao et al., 2021; Chen et al., 2023). Senior executives, therefore, hold conflicting views on whether AI represents a strategic necessity or an uncertain expenditure. A survey conducted by Deloitte identifies proving AI's business value to the stakeholders as the most significant challenge when initiating AI projects (Mittal & Ammanath, 2022). Hence, this leads us to question when AI investment will truly begin to pay off.

In 2022, the percentage of firms reported having lower returns than expected when implementing AI is 22%, a significant increase from 17% in 2021 (Mittal & Ammanath, 2022). These statistics show that more firms are worried AI investments may not deliver the returns they had expected. Although there are firms that perceive AI's potential as a tool for operational efficiency and competitive positioning, a minority of them are worried about possible implementation challenges, workforce disruptions, and data privacy risks (Cao et al., 2021).

AI has been frequently highlighted as an innovative technology, but the values it brings may have been exaggerated by the media to capture public interest. This media attention may create hype and overly positive perception of AI benefits among investors and business executives (Mihet & Philipon, 2019). At the same time, firms investing in AI often choose not to disclose their efforts until the gains are tangible (Lee et al., 2022). Additionally, some firms mention AI in their annual reports to shape investor perception. This practice is known as "AI washing," which refers to the practice when firms falsely claiming their use of AI to mislead investors (U.S. Securities and Exchange Commission, 2024). Consequently, it is challenging for researchers and executives to determine when, and whether, AI pays off.

2.2. AI Investment and Firm Performance

Empirical research on AI's direct impact at the firm level remains relatively scarce and can be divided into two main streams. The first stream centres on the firm's internal operational and financial performance with the realised benefits from AI investment are captured through improvements in profitability, operational efficiency, and resource utilisation. Studies in this stream concentrate on how AI investments affect financial indicators by optimising costs and internal processes such as profit margins, return on assets, return on equity, and cost ratios (Cheng et al., 2025; Kim et al., 2022; Sulivan & Wambal, 2024; Sun & Jiao, 2024; Wamba-Taguimdje et al., 2020).

Wamba-Taguimdje et al. (2020) examine how AI capabilities improve performance at both the process and organisational levels across several business lines. Their findings highlight that a successful AI implementation can reduce operational complexity and firms' reliance on paper-based workflows (Wamba-Taguimdje et al., 2020). The automation through AI optimises resource usage by minimising manual intervention to improve accuracy in time-consuming processes (Abduljabbar et al., 2019; Wamba-Taguimdje et al., 2020). This aspect of AI is defined as AI-enabled automation capability, which enhances firm performance by enabling firms to adjust internal operations and better respond to market changes (Sullivan & Wamba, 2024).

Another important capability of AI is its analytics capability (Sullivan & Wamba, 2024), which enables firms to process vast amounts of information and analytics tasks (Huang & Rust, 2021; Ramachandran et al., 2022; Sullivan & Wamba, 2024). On the one hand, AI-powered tools can analyse sentiments in internal communication data and assess employee performance to improve productivity (Ramachandran et al., 2022). This is crucial for firms as employee productivity is a critical factor in firm success, with some studies emphasising human capital as a key mediator in the relationship between AI investment and firm performance (Babina et al., 2024; Kassa et al., 2025; Mishra et al., 2022).

AI deployment develops competitive advantages by improving employee growth and their productivity, enhancing overall firm outputs (Dong et al., 2025; Kassa et al., 2025). These findings challenge fears that AI will replace human workers since AI integration can serve as a complementary tool and improve labour skills instead of replacing them. Employees with AI skills enable firms to innovate more effectively, which contributes to firm growth (Babina et al., 2024). As employees are firm intangible assets, AI strengthens these internal resources by improving their innovation, expertise, and learning abilities (Babina et al., 2024; Dong et al., 2025; Kassa et al., 2025).

On the other hand, regarding external data usage, AI-enabled analytics capability allows firms to analyse market patterns and predict emerging market trends in real-time, providing firms with a forward-looking perspective (Huang & Rust, 2021). This is referred to as firm resilience, which is the ability to integrate internal and external resources to respond quickly to change. Moreover, AI infrastructure and AI-driven skilled workforce strengthen firm resilience and allow firms to better mitigate the adverse situations, leading to financial gains (Kassa et al., 2025; Sharma & Kumar, 2024). In addition to boosting economic performance, AI investment also contributes to sustainability goals by reducing operational costs and improving environmental performance (Liu et al., 2025).

Prior literature supports the positive impacts of AI investment on firm financial performance (Chen et al., 2023; Cheng et al., 2025; Dong et al., 2024; Kassa et al., 2025; Kim et al., 2022; Liu et al., 2025). However, instead of viewing firm outputs as dynamic outcomes over the years, most studies focus on the average static results. This leads us to question when these gains begin to be realised. Using revenue growth as one of the measurements for firm performance, Lee et al. (2022) find that firm revenue increases significantly when the level of AI adoption increases. Sullivan & Wamba

(2024) analyse firm performance and innovation of AI-adopting firms using survey and panel data, but their study only tracks the performance in four months.

Wamba-Taguimdje et al. (2020) use cross-sectional assessment to study the performance of firms that successfully integrate AI, but their study only provides the average results of AI influence on firm performance. Even so, there are papers that explore the dynamic impact of AI investment on firm-level outcomes. For instance, Babina et al. (2024) employ long-difference regression to measure the change in firm performance after 8 years of AI integration, but this method analyses the effect at a specific point of time after the investment. Even research that uses longitudinal data acknowledges limitations in capturing long-term effects. Huang & Lin (2025) analyse firm profitability after AI adoption from 2010 to 2017, but they are unable to prove the long-term performance of AI due to the timing of data collection.

As a result, there is a theoretical gap in understanding whether the benefits of AI investment are tangible immediately or take longer to be realised. Indeed, empirical findings of Sun & Jiao (2024) suggest firms require approximately two years since the initial year of investment to realise the maximum performance benefit. Lee et al. (2022) report that low-intensity AI adoption at the initial stage of adoption has no significant effect on short-term revenue growth, suggesting AI investment brings no impact in the short term.

The iterative procedure of adopting new technologies necessitates well-established IT capabilities (Ransbotham et al., 2020). Due to its impact on people's ability to effectively perform high-skilled tasks or the mismatch between supply and demand of skilled AI workers, it takes time to fully integrate a whole new system (Lee et al., 2022; Uren & Edwards, 2023). Previous studies underscore a time lag between mental acceptance and actual technology adoption, which may explain why it likely takes more than one year for the technological investments' benefits to be realised when evaluating firm performance (Bohlen, 1964; Khallaf et al., 2017). Lee et al. (2022) contribute to this direction with empirical findings suggesting a delay in productivity gains after AI investment.

Additionally, several studies highlight that firms do not immediately see these improvements. While AI initiatives cut the cost of goods sold and improve firm performance, the effects do not always occur immediately (Kim et al., 2022). With technological investments, the productivity benefits from these processes tend to appear in the later stages instead of in the initial stages (Lee et al., 2022). Supporting this, Sun & Jiao (2024) analyse the influence of AI investments on ROE, concluding that positive impacts follow a time lag, and immediate gains are not observed. Findings from the study of Reinking et al. (2015) suggest investment in emerging technologies is associated with a short-term decline in firm performance. Since AI is also an emerging technology, firms may expect a similar pattern in their financial performance when they invest in AI. This aligns with the Productivity Paradox of IT proposed by Brynjolfsson (1993), which indicates the short-term performance may be lagging due to mismeasurement, redistribution, and mismanagement.

As a result, we believe the performance benefits of AI are not immediate but will be realised in the long term. Based on the literature above, we formulate the following hypotheses:

H_1: AI investment is associated with negative firm performance in the short term.

H_2: AI investment is associated with positive firm performance in the long term.

2.3. AI Investment and Market Value

The second stream of current research on AI concentrates on market-based firm outcomes such as stock returns and market valuation. Researchers analyse market-based metrics, which reflect investor sentiment and expectations about future firm growth, in addition to accounting-based indicators (Dong et al., 2025; Huang & Lin, 2025; Lui et al., 2022; Mishra et al., 2022). Investor confidence and market stability are sensitive to market volatility; however, prior studies highlight that AI can act as a key driver in reducing market volatility by enhancing firms' capabilities in risk management and predictive modelling (Dong et al., 2025). As market volatility decreases, firm market value tends to increase. Additionally, when firms implement AI, their business productivity and innovation – as well as investor expectations of future growth – increase, which raises stock prices and, consequently, market valuation. (Huang & Lin, 2025). Integrating AI into business processes improves operational efficiency and reduces the stock price crash risk through enhanced internal control (Li et al., 2024; Mishra et al., 2022; Schreieck et al., 2024). Since AI-enabled predictive capability allows firms to capture new opportunities more quickly than their competitors, their market returns also become better (Agrawal et al., 2022; Sullivan & Wamba, 2024).

Nevertheless, as with firm performance, the positive impacts mentioned above are static as current literature does not analyse its dynamic effects. Some studies suggest that AI investment announcements have negative short-term effects on market value. For instance, Lui et al. (2022) employ an event study approach to examine how AI investment announcements affect firms' abnormal stock returns. The results suggest an immediate negative impact on firm market value at the day the AI investment announcements were made. Song et al. (2025) suggest negative stock market reactions towards AI service failures may decrease firm value, but they also note that their methodology can only capture the financial impacts in the short term and does not provide insight into the long-term effects (Song et al., 2025). Due to the costly capital required and the uncertainty at the beginning of a new technology investment, the adverse reactions of the investors are understandable. However, since the costs incurred during the initial stage of AI investment are not permanent and these papers capture only short-term investor reactions, it is not certain whether AI-driven gains persist in the long run.

Meanwhile, several studies suggest long-term positive impacts of AI-related announcements possibly because investors believe technological investment involves short-term costs and tend to generate long-term values (Hadi et al., 2023; Lui et al., 2022; Schreieck et al., 2024). As a result, investors may perceive AI investment as positive news for a firm in the long run, leading to a rise in long-term market value (Lui et al., 2022). Empirical research suggests that firms implementing AI-driven financial and risk management strategies experience higher market capitalisation, total assets, and net tangible assets (Huang & Lin, 2025). Firms that invest in AI for improving product innovation and automating business processes have better market valuation growth (Babina et al., 2024). However, the research does not examine whether these effects continue in the following years.

When firms invest in new technology, their assets increase, but so do expenditures, resulting in reduced cash flow (Lui et al., 2022). As a result, investors often react negatively to such announcements as they expect a decline in firms' future cash flow. Nonetheless, these immediate reactions reflect short-term expectations rather than explaining whether the technological investment will bring long-term cash flow and value (Khallaf et al., 2017). In the later phases, investors may compare the short-term cost incurred from AI investment with the long-term returns that they expect it to bring. If they expect the benefits will outweigh the costs, the firm market value will increase (Lui et al., 2022). Babina et al. (2024) support this direction by highlighting the lagged effect on employees' stock market valuations when their firms invest in AI. These delays in market returns suggest the positive impacts of AI will begin to be realised after several years. The findings of Bae & Kim (2003) reinforce the idea that IT investments contribute to increasing a firm's market value over the long term. Thus, we formulate the following hypotheses:

H_3: AI investment is associated with negative firm market value in the short term.

H_4: AI investment is associated with positive firm market value in the long term.

2.4. Theoretical Gaps

2.4.1. Lack of Generalisability

Although current literature on AI's impact at the firm level explains how it improves organizational performance, the majority concentrates on country-specific markets. For instance, Cheng et al. (2025) and Li et al. (2024) examine firms' business operations after AI implementation. Nevertheless, their research mainly analyses firms in the Chinese market. Chen et al. (2023) study the managers' perceptions of AI usage to investigate how digital transformation strengthens business operations during a crisis. At the same time, they acknowledge their limitations in generalisation because the managers in their study are from a single country (Chen et al., 2023).

Similarly, despite their investigation of AI's role in enhancing firm agility and automation, the empirical findings of Sun & Jiao (2024) are limited to Chinese firms. The study of Liu et al. (2025) has the same limitation with their focus on the Chinese market when assessing AI's influence on business performance and corporate sustainability. In addition, Sullivan & Wamba (2024) analyse the responses of firms to market changes toward AI in the UK and France. Kassa et al. (2025) measure the impact of AI adoption on an Ethiopian firm, and Lee et al. (2022) investigate firms in South Korea to figure out when AI pays off. Although these papers provide valuable information towards AI's impact, their narrow research scopes limit the generalisability of their findings. By analysing firms in the U.S. market, our study can capture the effects over time, thereby extending current literature by providing insights to the U.S. market.

2.4.2. Lack of Causal Inference

Most existing studies of AI investment use methodologies that do not allow causal inferences. For instance, panel studies (Liu et al., 2025; Mishra et al., 2022; Sullivan & Wamba, 2024), surveys (Cao et al., 2021; Chen et al., 2023; Kassa et al., 2025; Sharma & Kumar, 2024; Sullivan & Wamba, 2024), quantitative analyses (Li et al., 2024; Sun & Jiao, 2024), and case studies (Wamba-Taguimdje et al., 2020). On the other hand, the studies by Kim et al. (2022) and Huang & Lin (2025) employ a DID analysis to identify the causal impact of AI investment on firm outcomes by comparing changes between treatment and control groups. However, their research designs focus on two static periods and do not provide insight into how the impact changes years by years. By employing staggered DID study design with relative time framework, this study measures effects relative to the timing of AI investment, allowing for stronger causal inference.

The literature review highlights that the impacts of AI investment on firm performance and market valuation in the short term and long term remain unexplored. Therefore, this study extends current literature by investigating the dynamic impact of AI on firms. Note that as managerial short-term orientation refers to a focus on performance within the current budgeting period (one year), in this study we define short-term impact as one year or less while long-term impact as any period that longer than one year (Van der Stede, 2000). Hence, we present the conceptual framework in *Figure 1*, which visually illustrates the proposed hypotheses.

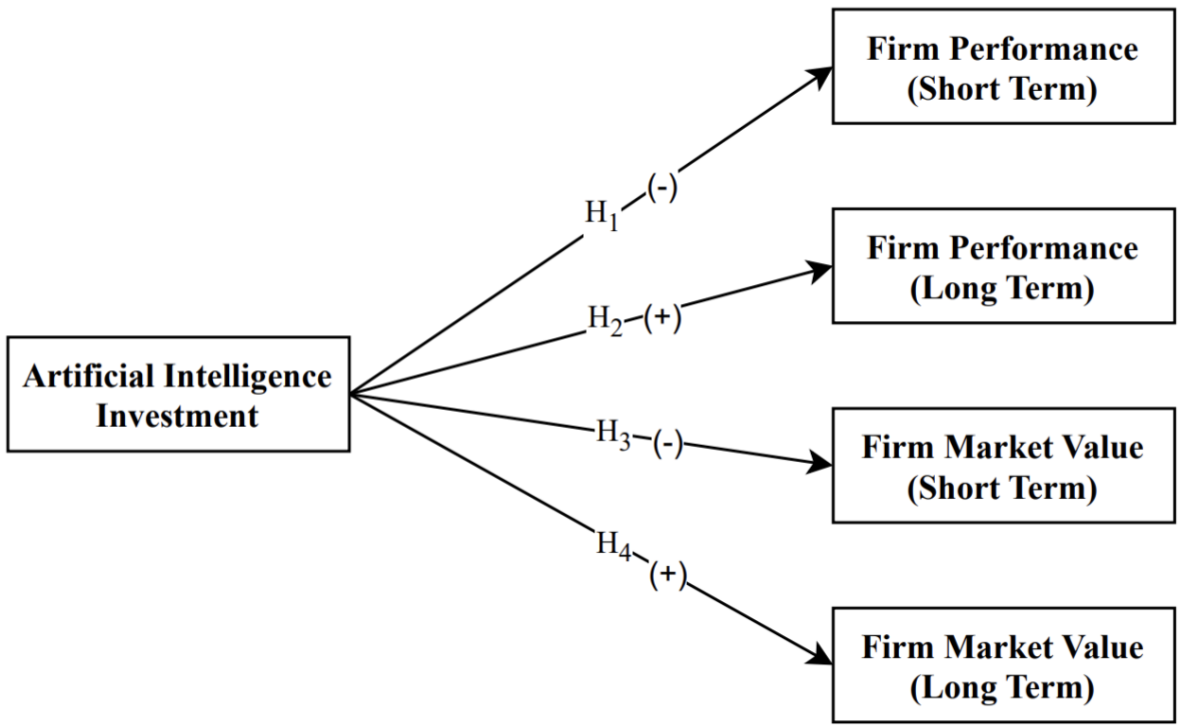

Figure 1. Conceptual Framework

This conceptual framework provides a foundation for examining when the impacts of AI investments on firms start to be realised and the duration of these effects. The framework supports a comprehensive understanding of both the theoretical implications and the practical relevance of AI investment at the firm level to address the research questions at the beginning of this study.

3. Methodology

This chapter describes the research design to answer the research questions in the following order. First, the processes of data collection and data preprocessing are described. Second, from the final dataset, the construction of dependent variables, independent variables and control variables are explained in detail with rationales. Finally, the staggered DID model is presented, and its assumptions are discussed.

3.1. Data

As mentioned in the previous chapter, this study focuses on publicly listed firms in the U.S. market to improve the generalisation of our study due to the following reasons. According to the Global Innovation Index, the United States of America is one of the top global leaders in innovation in the year 2024 (World Intellectual Property Organisation., 2024). Therefore, we expect a significant number of firms investing in AI to be concentrated in this market. Publicly listed firms in the U.S. are subject to the "listing standards", including the filing of standardised annual reports through the SEC's EDGAR (U.S. Securities and Exchange Commission., 2025). Furthermore, firms' reports must follow structured formats, are written in English, and are publicly accessible. This transparency makes the U.S. market suitable for our empirical research.

We collect data from three sources. First, data for AI-investing firms is constructed from the S&P Kensho AI Enablers & Adopters Index, which belongs to the S&P Dow Jones Indices. We select this index as S&P Dow Jones Indices is widely recognised for producing stock market indices as benchmarks, ensuring the validity of the dataset. The dataset was obtained under an academic-use agreement with S&P Global on January 15, 2025, and contains firm-level information such as ticker symbols, company names, and market capitalisations. The S&P Kensho AI Enablers & Adopters Index measures the performance of firms that have invested in AI, either by developing AI technologies as core products, adopting them to improve internal business processes or both (S&P Dow Jones Indices, 2024). However, within the scope of this study, we do not distinguish between AI investment types since our focus is on the fact that the firm has invested in AI. We remove firms that were either delisted or acquired by another firm or not active during the observation period from the dataset to ensure the consistency of all firms in the treatment group. This adjustment results in an initial treatment sample of 108 firms.

Second, the control group is constructed from firms listed in the S&P 500 Index. The dataset containing firms in the S&P 500 Index was retrieved from Kaggle on January 15, 2025, with the dataset reported to be updated daily (Kaggle, 2025). The control group in this study consists of firms in the S&P 500 Index that did not invest in AI during the observation period. On the same date of retrieving data, the minimum market capitalisation among firms in the S&P 500 Index is approximately $15 billion (S&P Global, 2025). As a result, all firms in the treatment group with market capitalisations below this threshold are excluded to ensure the two groups are comparable, and the list of removed firms in the treatment group is shown in *Appendix B*. While this adjustment reduces the overall sample size and may affect representativeness, it helps mitigate bias between the treatment and control groups. Hence, the final treatment group comprises 61 firms. A full list of firms investing in AI is shown in *Table 1*. We then randomly select firms listed in the S&P 500 Index that are not included in the S&P Kensho AI Enablers & Adopters Index, resulting in a control group of 61 firms. The list of 122 firms is shown in *Appendix D*.

Third, firm-level longitudinal data covering the years 2013 to 2023 are collected through Wharton Research Data Services (WRDS), which includes financial and market variables from Compustat and the SEC's EDGAR database.

Firm Name	**Investment Year**	**Firm Name**	**Investment Year**
Agilent Technologies Inc	2019	Mercadolibre Inc	2022
Adobe Inc.	2019	Facebook Inc A	2018
Autodesk Inc	2018	Microsoft Corp	2018
C3.ai, Inc. Class A	2021	NIO Inc-ADR	2020
Altair Engineering Inc.	2020	Northrop Grumman Corp	2019
Advanced Micro Devices	2018	ServiceNow Inc.	2022
ANSYS Inc	2018	NetApp Inc	2022
Aerovironment Inc	2022	NetEase Inc ADR	2018
Broadcom Inc	2022	Nvidia Corp	2018
Aspen Technology Inc	2022	Oracle Corp	2018
Alibaba Group Holding Ltd ADR	2021	Open Text Corp	2018
Baidu.com ADR	2018	UiPath, Inc.	2021

Blackbaud Inc	2019	Pure Storage Inc	2020
Charles River Laboratories	2019	PTC Inc	2020
Cisco Systems Inc	2020	QUALCOMM Inc	2022
Dover Corp	2019	SAP SE ADR	2018
ExlService Holdings Inc	2022	Super Micro Computer Inc	2022
General Dynamics	2020	Snap, Inc.	2019
Globant SA	2023	Stellantis N.V.	2022
Alphabet Inc C	2018	STMicroelectronics NV NYShs	2019
Honeywell Intl Inc	2020	Seagate Technology	2021
Intl Business Machines Corp	2018	Stryker Corp	2019
Infosys Limited ADR	2022	Teradata Corp	2022
Ing Groep NV ADR	2018	Toyota Motor Corp ADR	2019
Intel Corp	2018	Tesla, Inc	2019
KBR Inc	2021	Visteon Corp	2019
KLA Corporation	2020	VMware Inc A	2022
LendingClub Corp	2021	WEIBO CORP ADR	2019
Lattice Semiconductor Co	2019	Zebra Technologies Corp	2022
Mastercard Inc A	2021	Zimmer Biomet Holdings Inc	2023
Medtronic plc	2019		

Table 1. Firms Investing in AI and Investment Year

3.2. Independent Variable Construction

Our primary independent variable in this study is AI investment, which is determined by the inclusion of firms in the S&P Kensho AI Enablers & Adopters Index. Nevertheless, as we employ the relative framework, it is essential to identify the initial period firms invest in AI. The S&P Kensho AI Enablers & Adopters Index dataset contains the date assigned to each firm and is named “Effective Date”. The date represents the point when a firm was added to the S&P Kensho AI Enablers & Adopters Index or when adjustments were made to its classification or weighting based on the S&P Kensho Indices Methodology (S&P Dow Jones Indices, 2022).

However, their methodology does not indicate whether this “Effective Date” represents the initial date that firms invest in AI or that firms announce to invest in AI. Moreover, as discussed in the Literature Review chapter, firms may mention AI investment in their annual reports to intentionally influence investors’ behaviours without actual investments. Hence, we consider three approaches to ensure the validity of our independent variable.

The first approach involves conducting case studies and surveys with firms listed in the S&P Kensho AI Enablers & Adopters Index. This approach has practical limitations as reaching high-level managers is challenging due to time and confidentiality constraints. Additionally, it does not provide historical data, making it unsuitable for measuring the effects of AI investment over time. An alternative method is a sentiment analysis of external media coverage. However, media reports are not subject to verification and may exaggerate AI investments. For these reasons, we employ textual analysis of firm disclosures from SEC's EDGAR database using large language models (LLMs). The approach addresses the limitations of case studies, surveys and media sentiment analysis by using direct firm disclosures, which are available electronically and audited under regulation in the U.S. market (Li, 2010). In addition, the SEC's EDGAR database provides comprehensive longitudinal data of publicly listed firms in the U.S. market, allowing us to examine the dynamic effects of AI usage before and after the investment period.

3.2.1. Text Extraction Using Large Language Model

Before conducting a textual analysis, we first retrieve firm disclosures and extract only the sections related to AI investments as annual reports contain also information that is out of scope of this study. We employ the "edgar" package in R to download annual reports filed by publicly traded firms with the U.S. SEC via the EDGAR database because this package has a built-in function that enables us to download bulk reports in a short time (Lonare & Patil, 2025). We use company-specific Central Index Key (CIK) numbers to download filings for the 10-year period in plain text format. Note that for U.S. based firms, we retrieve Form 10-K reports while for foreign private issuers, we collect Form 20-F reports (U.S. Securities and Exchange Commission., 2013).

The initial plain text files contain embedded markup tags and metadata sections, making the content noisy and the files too large for an efficient textual analysis. Thus, we perform an additional step to clean the files and enhance text quality by using R. First, each file is read line-by-line and then consolidated into a single continuous string to allow uniform processing. Then, all markup tags (XML, XBRL, and HTML), metadata (<SEC-HEADER> and <SEC-DOCUMENT> blocks), line breaks and white spaces are removed as they do not contain meaningful textual content. Finally, we convert all text to lowercase to ensure case-insensitivity during the textual analysis.

Due to the high volume of the disclosures, it is inefficient to extract AI-related text from these documents manually. Hence, we employ a large language model (LLM) for text extraction because LLMs have been proven to process large scale of financial text with a greater speed and consistency, making it more efficient when extracting text from documents (Loughran & McDonald, 2020). Moreover, we select OpenAI's ChatGPT as the primary LLM for this study because ChatGPT is the most mature LLM in the market (Artificial Analysis, 2025). As of January 16, 2025, GPT-o1 is the most advanced model of ChatGPT, but it does not support direct document uploads into the ChatGPT interface (OpenAI, 2025). This means it is impossible to extract AI-related text from firms' annual reports if we use this model as these documents need to be uploaded for scanning. Thus, we opt for GPT-4o which is the second most advanced model. Although it has lower reasoning capabilities, the GPT-4o model allows data extraction from documents and images with high validity and reproducibility (Motzfeldt Jensen et al., 2025; Wulcan et al, 2025). The filings are uploaded to the ChatGPT interface for text extraction with a prompt requiring relevant sections specifically mentioning AI investments are quoted and displayed within the interface.

3.2.2. Textual Analysis Using Large Language Model

We then analyse the extracted text to verify our assumptions. The primary purpose of this analysis is to verify whether the year a firm first mentioned their AI investment is prior to the "Effective Date" in the S&P Kensho AI Enablers & Adopters Index. This verification is necessary because if firms did not mention AI investment in their annual reports before the "Effective Date" in the S&P Kensho AI Enablers & Adopter Index, the construction of our independent variable would not be valid. Thus, we assume that firms listed in this index have invested in AI and that the recorded start year of AI investment is accurate. If either assumption is violated, the start date will be adjusted, or the firm will be excluded from the study.

In the process of textual analysis, we continue to use LLM-based tool. This time, we select model GPT-o1 due to its most advanced reasoning capabilities and better thinking power for more difficult problems among current models of OpenAI (OpenAI, 2025). To improve the validity and reliability of this method, we verify a random sample of 10 outputs from the model by manually checking whether the AI investment years are accurate, and whether AI investment-related statements are in the firms' annual filings. Our manual validation process confirms the LLM's outputs are valid.

The analysis identifies patterns in firms' AI-related statements and assesses whether their engagement in AI truly occurred before the inclusion date in the S&P Kensho AI Enablers & Adopters Index. Through this process, we discover two interesting facts. First, most firms used the word "invest" when discussing their AI-related activities rather than explicitly stating that they were adopting AI or enabling AI. Second, despite minor variations, every firm in the dataset mentioned AI in its filings before the year listed in the dataset. The descriptive statistics of the year in the dataset and the year through textual analysis are shown in *Table 2*.

Descriptive Statistics	Min	1st Quartile	Median	Mean	3rd Quartile	Max
Investment Year (dataset)	2018	2019	2020	2020	2022	2023
Investment Year (textual analysis)	2015	2018	2019	2020	2021	2023

Table 2. Differences in Descriptive Statistics of Investment Years

The results align with our initial assumptions that firms listed in the AI Kensho Enablers & Adopters Index mentioned their strategic AI investments in their annual filings. Moreover, the years they first mentioned these investments are prior to the date included in the dataset. Thus, we proxy the year in the "Effective Date" as the intervention date as it accurately reflects the period at which firms invest in AI.

3.3. Dependent Variable Construction

3.3.1. Firm Performance

We consider two dependent variables to examine the impact of AI on firm outcomes. Our first dependent variable is financial performance, which plays an important role when assessing how well firms perform post-investment. In addition, financial performance analysis provides investors and business leaders with a risk assessment and necessary information for decision-making (Huang & Lin, 2025). As a result, understanding whether these efforts translate into tangible performance improvements is essential for justifying the investment to stakeholders. In this study, we use two profitability ratios to measure firm financial performance: return on equity (ROE) and return on assets (ROA). We believe when AI investments positively impact firm performance, it will be reflected in their profits. Profitability ratios have been commonly used by scholars to assess a firm's business success or performance (Barnes, 1967; Sabherwal & Jeyaraj, 2015). In this study, ROE and ROA are calculated following the calculation approach of Ross et al. (2017).

ROE is a robust indicator that reflects a firm's operation efficiency and long-term profitability relative to shareholder equity (Gao et al., 2023). Since ROE captures both operational effectiveness and financial leverage, it is commonly used in investment analysis and corporate performance evaluation (Al-Matari et al., 2014). In this study, ROE is calculated as net income (Compustat item NI) divided by total shareholders' equity (Compustat item TEQ). The calculation is presented below where the subscript i denotes the individual firm and t refers to the specific year:

$$ROE_{i,t} = \frac{Net\ Income_{i,t}}{Total\ Shareholders'Equity_{i,t}}$$

Meanwhile, ROA reflects the efficiency of firms in generating profits from their assets (Khrawish, 2011). ROA is calculated as net income (Compustat item NI) divided by total assets (Compustat item AT). The calculation is presented below where the subscript i denotes the individual firm, while t refers to the specific year:

$$ROA_{i,t} = \frac{Net\ Income_{i,t}}{Total\ Asset_{i,t}}$$

3.3.2. Firm Market Value

The second dependent variable is firm market value, which reflects investor expectations regarding a firm's future growth. Unlike accounting-based measures, market value is forward-looking (Al-Matari et al., 2014). As a market-based indicator, firm market value provides insights into how shareholders perceive a firm's growth potential, and its future earnings (Anagnostopoulou, 2008). This distinction is essential because it allows the analysis to capture how AI investment is perceived and priced by the market, thereby providing insight into whether such strategic initiatives are viewed as value-creating by shareholders, independent of immediate operational outcomes.

In this study, we use Tobin's Q as a proxy for firm market value following the calculation approach described by Flammer & Bansal (2017). This indicator is widely used to evaluate return on investment as it reflects investor expectations about the market valuation and efficiency of a firm by comparing the market value of a firm's assets to their book value (Gao et al., 2023). Tobin's Q is computed as the total assets (Compustat item AT) plus the market value of equity, minus the book value of equity (Compustat item CEQ) and deferred taxes and investment tax credits (Compustat item TXDITC), divided by the total assets. The market value of equity is calculated as the number of shares outstanding (Compustat item CSHO) times the stock price (Compustat item PRCC_F). The calculation is as follows, where the subscript i denotes the individual firm, t refers to the specific year, BV is the book value, and MV is the market value:

$$Tobin's\ Q_{i,t} = \frac{Total\ Assets_{i,t} + MV\ of\ Equity_{i,t} - (BV\ of\ Equity_{i,t} + Deferred\ Taxes_{i,t} + Investment\ Tax\ Credits_{i,t})}{Total\ Assets_{i,t}}$$

3.4. Control Variables

Since larger firms have greater access to financial resources and benefit from economies of scale, firm size may impact firms' abilities to invest in AI technologies (Irwin et al., 1998; Reinking et al., 2015). Therefore, we control for firm size to isolate the effect of AI investment accurately. The firm size is calculated by the natural log of the total assets of firm i in year t (Astakhov et al., 2019):

$$Firm\ Size_{i,t} = ln(Total\ Assets_{i,t})$$

In addition, we introduce firm fixed effects and year fixed effects to control the time-invariant factors within a firm and within a year that can affect the relationship of AI investment on firm performance and firm market value. Firm fixed effects can be firm working culture, managerial style, or location, whereas year fixed effects can be macroeconomic change or policy shifts.

3.5. Staggered Difference-in-Difference

This study examines the dynamic relationship of AI and firms from 2013 to 2023 by employing a staggered DID study design. The DID design is a quasi-experimental method that allows for causal inference using observational data without randomisation. While the conventional DID design compares control and treatment groups only in two different periods (pre-treatment and post-treatment), our study uses an extended framework with a relative time model wherein the treatment is implemented in multiple periods (Burtch et al., 2018). The staggered design allows us to examine the causal effect of a treatment, in this case AI investment, that takes place across multiple periods rather than all at once. In this study, the treatment group contains firms that invested in AI during the observation period. Whilst the control group consists of two types of firms, those that never invested in AI and those that had not yet made the investment by the time the treatment occurred.

This approach enables us to compare firms at different stages of AI investment and better understand its impact over time. Moreover, the longitudinal structure of the data allows us to assess the parallel trend assumption, an essential validity check that will be discussed in detail in the Results chapter (Bertrand et al., 2004). In this study, we concentrate on the dynamic effect of two groups in multiple pre- and post-AI investment periods. Consequently, we employ a staggered DID event study design using a linear two-way fixed effects (TWFE) model. TWFE is selected as the estimator as it provides consistent results even with heterogeneous treatment over time (Rüttenauer & Aksoy, 2024).

This study compares the differences in firm performance and firm market value before and after the AI investment year between firms that invested in AI technologies with those did not or have not implemented AI yet by using the relative time framework. Due to the sparsity of observations at the tails of the event window, we collapse all relative time periods earlier than -6 into a single dummy and all periods later than four into another dummy (Burtch et al., 2018). The relative time dummies before and after being collapsed are shown in *Appendix C.* Therefore, in this study, the impacts of AI investment before 6 years and after 4 years on the firm's performance and market value are evaluated. The staggered DID model using TWFE takes the form:

$$Y_{i,t} = \sum_{j} \beta_j (j_{i,t}) + X_{i,t} + \alpha_i + \gamma_i + \varepsilon_{i,t}$$

In this model, $Y_{i,t}$ denotes the performance or market value of firm i in year t, $j_{i,t}$ captures the interaction term of the treatment dummies and the relative timing of firm i at year t with respect to a firm's AI investment year with j = 0 corresponding to the investment year, j < 0 representing pre-treatment years, and j > 0 capturing post-treatment dynamics. β_j is the coefficient of each period. Note that, because never-treated firms do not have an investment year, this term is set to 0 for all their observations by default. This ensures they remain in the control group for our regression analysis as leaving them as missing values may result in their exclusion from the estimation. $X_{i,t}$ is the control variable of firm i in year t while α_i represents firm fixed effects and γ_i represents year fixed effects. The standard errors are clustered at the firm level to account for the serial correlation (Angrist and Pischke, 2014; Bertrand et al., 2004; Gu et al., 2024). The description summary is shown in *Table 3*.

Variables	**Description**
$Y_{i,t}$	The dependent variable for firm i in year t, representing either ROE, ROA, or Tobin's Q
$j_{i,t}$	The interaction term of relative time dummies and treatment dummies capturing the dynamic effect of AI investment across time (time until the start of the investment). For instance, if a firm invested in AI in 2017, this term is −2 when calendar year is 2015 and 3 when calendar year is 2020. This term equals 0 for all years if firm i did not invest in AI during the observation period.
β_j	The coefficient of relative time dummies
$X_{i,t}$	Control variable of firm i in year t
α_i	Firm fixed effects controlling for time-invariant characteristics specific to each firm.
γ_t	Year fixed effects controlling for time-specific shocks that affect all firms.
$\varepsilon_{i,t}$	The error term capturing unobserved factors affecting the outcome for firm i in year t

Table 3. Variables Description

Data of ROE, ROA and Tobin's Q are obtained through the Compustat database, resulting in 1,308 firm-year observations. *Table 4* shows the encoded variables for analysis. The dependent variables include ROE, ROA, and Tobin's Q, all measured as continuous decimal values. INVESTMENT is a binary indicator, which equals 1 if a firm invested in AI during the observation period and 0 otherwise. INVESTMENT_YEAR and YEAR are integer values representing the year of AI investment and the calendar year of observation, respectively. REL_TIME is the relative time dummy measuring the number of years relative to the firm's AI investment year. TICKER is firms' ticker symbol, serving as the firm identifier.

Variable Name	Description	Data Type
ROE	Return on equity	Continuous (decimal)
ROA	Return on assets	Continuous (decimal)
TOBIN	Tobin's Q	Continuous (decimal)
AT	Total assets	Continuous
REL_TIME	Relative time (calendar year of observation minus AI investment year)	Integer (can be negative)
INVESTMENT	AI investment status (1 if invested during the observation period, 0 otherwise)	Binary (0/1)
INVESTMENT_YEAR	Year of AI investment	Integer
YEAR	Calendar year of observation	Integer
TICKER	Firm identifier (stock ticker symbol)	Categorical (string)

Table 4. Description of Encoded Variables

Table 5 displays the descriptive statistics of the main variables in this study, with N is the number of observations and SD is the standard deviation. From a sample of 1,308 firm-year observations, the mean ROE is 0.451 with a standard deviation of 4.78, indicating high variability. Tobin's Q is also volatile with a standard deviation of 2.34, and its average mean is 2.78, ranging from 0.76 to 27. Meanwhile, ROA is less volatile with a mean of 0.0614 and a standard deviation of 0.0901.

Variable	N	Mean	SD	Min	Max
ROE	1,308	0.451	4.78	-31	144
ROA	1,308	0.0614	0.0901	-0.1	0.65
TOBIN	1,308	2.78	2.34	0.76	27
AT	1,308	187,796	458,567	161	3,875,393
INVESTMENT_YEAR	1,308	970	1010	0	2023
INVESTMENT	1,308	0.48	0.5	0	1
REL_TIME	1,308	-0.74	2.33	-6	4

Table 5. Descriptive Statistics of Encoded Variables

INVESTMENT_YEAR represents the initial year that AI firms announced their investment in AI, with 0 is the value for non-AI firms. INVESTMENT has a mean of 0.48, meaning approximately 48% of observations are AI-investing firms and 52% are non-AI firms. AT represents firm total assets and will be log transformed when running the regression models. REL_TIME captures the number of years relative to AI investment, with a mean of -0.74 and ranges from -6 to 4.

3.6. Staggered Difference-in-Difference Assumptions

Before analysing the main results, we first assess the validity of our study. The validity of the DID research design is based on three key assumptions (Gutt, 2024). In the following section, we discuss the meaning of each assumption and our argument in the context of this study.

- **Parallel Trend Assumption**

The first assumption is the parallel trend assumption or common trend assumption. This is the most crucial assumption in DID study design (Angrist & Pischke, 2014; Callaway & Sant' Anna, 2021; Goodman-Bacon, 2021; Sun & Abraham, 2021). The assumption requires that in the absence of treatment, the treatment and control groups must move in parallel before the intervention otherwise any observed differences may be coincidental (Li et al., 2021). This assumption can be verified by visual inspection, meaning that if coefficients before the AI investment year are statistically insignificant and close to zero, the parallel trend assumption holds. In this study, we structure time relative to the AI investment event. Thus, our model can capture both pre-treatment trends and post-treatment effects.

- **Stable Unit Treatment Value Assumption (SUTVA)**

The second assumption is the stable unit treatment value assumption, which was developed by Rubin (1980) for causal inference in experimental or quasi-experimental design to ensure the validity of the study (Gertler et al., 2016). This assumption has two components. The first component is non-interference, indicating that the treatment status of any unit does not affect the potential outcomes of other units. This means the financial performance and market value of non-AI firms should not be impacted by the fact that other firms invested in AI. Indeed, it is unlikely that one firm's investment in AI affects the performance of other firms as the financial costs and gains of such technology investments are not transferable across firms. However, regarding the market value, when some news arrives in the market, whether being a good or bad news they tend to create chain reaction and lead to price volatility (Mamtha & Srinivasan, 2016; Kalotychou & Staikouras, 2009). Hence, we acknowledge a potential violation of firm market value due to spillover effects of price volatility, but it should not be a concern in this study as these effects are generally short-term (Kalotychou & Staikouras, 2009).

The second component of SUTVA is no variation, meaning that the treatments for all units must be comparable. In our study, this implies that the AI investments should be homogenous across firms whereas it is indeed a heterogeneous treatment since firms might invest in different types of AI with varying intensity and application domains. Nevertheless, as discussed in Methodology chapter we focus on the fact that firms invested in AI, meaning the treatment is a strategic decision instead of any specific form of AI. Furthermore, we consider the variation between firms by including firm fixed effects and controls for firm size and rely on the staggered DID design to identify the impact of treatment timing. As a result, we argue the treatment status is comparable for all firms and this assumption is not violated.

- **Conditional Independence Assumption**

The last assumption is conditional independence assumption, which states that the participation in the treatment group is conditionally random, and the treatment is independent from any potential outcomes (Cunningham, 2021). In the context of our study, it is unlikely that firms randomly invest in AI. Instead, strategic incentives such as financial gains, enhanced capabilities and productivity are the main factors motivate firms to invest in AI. These actual motivations raise the possibility of selection bias since they imply that firms deciding to invest in AI may systematically differ from those that do not. Therefore, we take additional steps to mitigate potential selection bias arising from our analyses. Our empirical models include firm and year fixed effects to control for time-invariant factors across firms and macro-level shocks over time. Moreover, we control for firm size, which is a time-varying firms' characteristic. This allows us to more credibly isolate the relationship between AI investment and firm performance and market valuation from confounding factors that could otherwise bias the estimated effects.

4. Results

This chapter presents our empirical findings regarding the effect of AI investment on firm performance and market value. We construct six different models to measure the impact and observe the differences when controlling for external factors that can affect the relationship between AI investment and firm outcomes. All six models are implemented using "fixest" package in R (Berge, 2021). We omit one year before AI investment when running regression to prevent multicollinearity and use this omitted year as a baseline period (Sun & Abraham, 2021). Due to the slight difference in dependent variables usage and the similarity between groups of models, the statistical regressions are aggregated into two main groups of models. For each dependent variable, two model specifications are estimated. Models 1, 3, and 5 serve as a baseline without control variables:

$$(1)\ ROE_{i,t} = \sum_{j} \beta_j (INVESTMENT_i * REL\_TIME_{i,t}) + \varepsilon_{i,t}$$

$$(3)\ ROA_{i,t} = \sum_{j} \beta_j (INVESTMENT_i * REL\_TIME_{i,t}) + \varepsilon_{i,t}$$

$$(5)\ Tobin's\ Q_{i,t} = \sum_{j} \beta_j (INVESTMENT_i * REL\_TIME_{i,t}) + \varepsilon_{i,t}$$

Whereas Models 2, 4, and 6 include control variables with both firm and year fixed effects.

$$(2)\ ROE_{i,t} = \sum_{j} \beta_j (INVESTMENT_i * REL\_TIME_{i,t}) + X_{i,t} + \alpha_i + \gamma_i + \varepsilon_{i,t}$$

$$(4)\ ROA_{i,t} = \sum_{j} \beta_j (INVESTMENT_i * REL\_TIME_{i,t}) + X_{i,t} + \alpha_i + \gamma_i + \varepsilon_{i,t}$$

$$(6)\ Tobin's\ Q_{i,t} = \sum_{j} \beta_j \left(INVESTMENT_i * REL_{TIME_{i,t}}\right) + X_{i,t} + \alpha_i + \gamma_i + \varepsilon_{i,t}$$

4.1. Main Results

Before interpreting the main results, we first assess the parallel trend assumption of our study. The graphical representations of the estimates in Model 5 using ROE, ROA, and Tobin's Q as dependent variables are shown in *Figure 2*, *Figure 3*, and *Figure 4*, respectively. The horizontal axis represents the relative time periods to the initial year of AI investment. Each black dot represents the estimated coefficient for a specific period, and the vertical bars indicate the associated 95% confidence intervals. The dashed vertical line marks the baseline period (one year before investment), which is omitted from the estimation.

Looking at the three plots, all estimated coefficients in pre-investment periods are close to zero and statistically insignificant. This means there are no pre-trends that affect the outcomes of treated firms, and the parallel trend assumption is not violated.

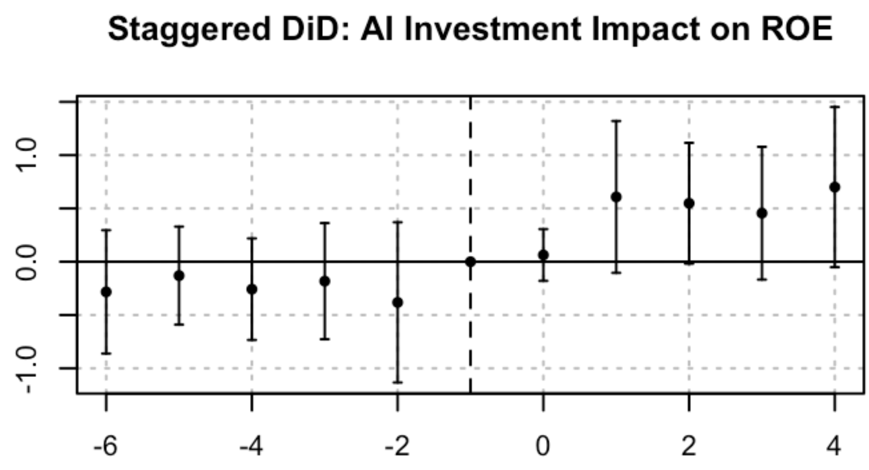

Figure 2. Plot of the Impact of AI Investment on ROE

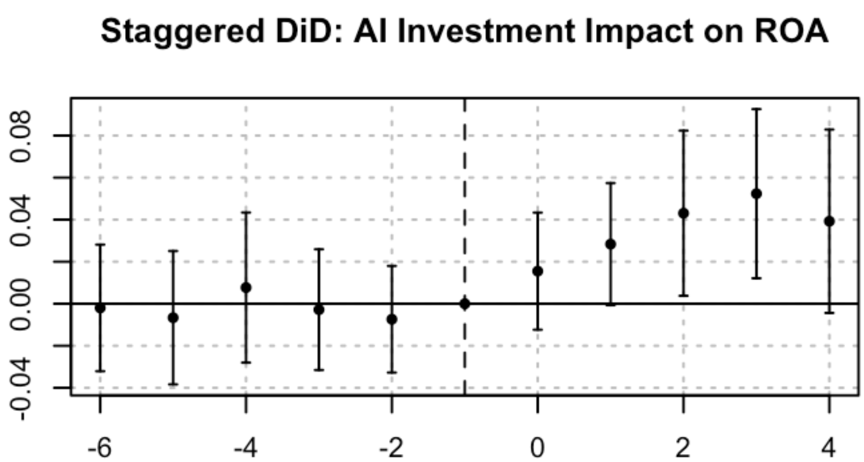

Figure 3. Plot of the Impact of AI Investment on ROA

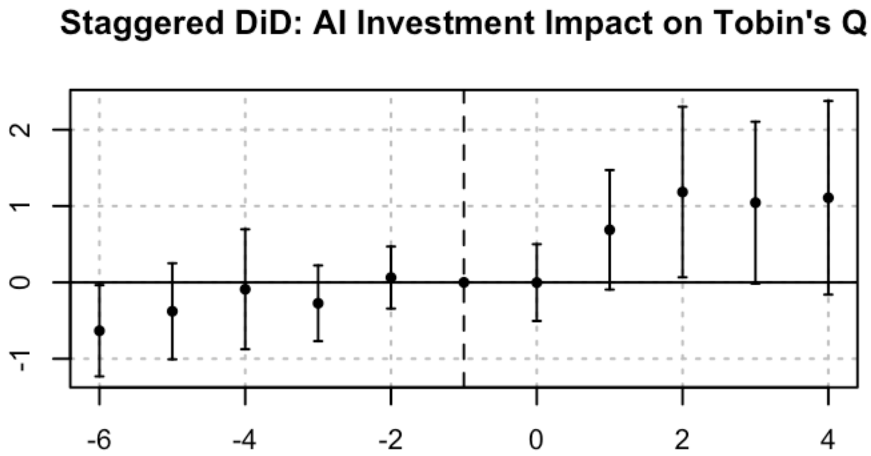

Figure 4. Plot of the Impact of AI Investment on Tobin's Q

Table 6 shows the regression results of all six models using three dependent variables. We begin by analysing the effect of AI investment on firm performance ROE as the first proxy in Model 1 and Model 2. *Table 6* shows that in the baseline model without firm size or fixed effects (Model 1), pre-treatment coefficients are generally negative or insignificant, except for 5 years and later pre-investment. A similar pattern can be seen in Model 2 with all estimates statistically insignificant, suggesting no strong evidence of pretreatment trends. This means the parallel trends assumption holds for ROE as a dependent variable.

In testing these hypotheses, we run all six models and observe their regression results.

H_1: AI investment is associated with negative firm performance in the short term.

H_2: AI investment is associated with positive firm performance in the long term.

H_3: AI investment is associated with negative firm market value in the short term.

H_4: AI investment is associated with negative firm market value in long term.

What can be seen in Model 1 is none of the estimates is statistically significant despite their positive effect after the investment year. Nonetheless, once firm size and fixed effects are introduced in Model 2, the post-treatment coefficients become statistically significant and higher with R-squared increasing from 0.00238 to 0.1308 accordingly. Specifically, one year after AI investment, firms that invested in AI experienced a 0.6081 percentage point increase in ROE relative to their own pre-treatment level, compared to the change in control firms ($p < 0.10$). This rejects Hypothesis 1 that the impact of AI on firm performance is negative in the short term. The positive effect remains in the second year (0.5425, $p < 0.10$) and becomes higher in year four (0.6912, $p < 0.10$). While being positive at 0.4435, the coefficient of ROE is not statistically significant in year three after the AI investment year. These empirical findings support Hypothesis 2 that the AI investment is associated with long-term improvements in firm performance in terms of ROE.

Turning to ROA, which is our second proxy for firm performance, we see a similar pattern. In Model 3 (without controls), coefficients of ROA before AI investment are small and insignificant, indicating no violation of parallel trend assumption. Post-investment estimates show a positive but weak effect, and the coefficients are only significant in year three (0.0382, $p < 0.05$) and later (0.0431, $p < 0.05$) after the year of AI investment. Once firm size and fixed effects are included (Model 4), the positive impact becomes stronger and statistically significant.

Particularly, in the first year after AI investment, ROA increases by 0.0267 percentage points ($p < 0.10$) relative to the pre-treatment period, compared to the change in control firms. This provides evidence to reject Hypothesis 1 that AI investment is associated with negative firm performance in the short term. The coefficients of ROA remain positive through year two (0.0413, $p < 0.05$), year three (0.050, $p < 0.05$) but lack statistical significance since year four. Like ROE, Model 4 with controls indicates a more robust relationship between AI investment and ROA, with R-squared increasing from 0.01408 to 0.58070. Consistent with the ROE regression, results of ROA support Hypothesis 2, suggesting that AI investment is associated with improvements in financial performance in the long term.

Finally, we examine firm market value after AI investment through Tobin's Q. In the baseline model (Model 5), pre-treatment coefficients are mostly insignificant, except for the year of AI investment showing a significant negative value (-1.528, $p < 0.01$). When controlling for firm size and firm-year fixed effects in Model 6, the regression results show more significant estimates post-investment. One year after AI investment, AI-investing firms have higher Tobin's Q by 0.6726 ($p < 0.10$). This rejects our Hypothesis 3 that AI investment is associated with negative firm market value in the short term. The effects remain positive with 1.166 in year two ($p < 0.05$) and 0.9748 in year three ($p < 0.10$). In year four and later, the results lack statistical significance in year four and later, but the effect remains positive with a value of 1.054. These results support Hypothesis 4, suggesting that the AI investment leads to positive market value over time. The R-squared supports the robustness of Model 6 when rising from 0.11764 to 0.66341 when adding controls.

Dependent Variables:	ROE		ROA		TOBIN	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Constant	0.2271***		0.0472**		3.642***	
	(0.0712)		(0.0194)		(0.3420)	
6+ years before AI investment	-0.1514*	-0.2577	0.0299	-0.0006	-0.3687	-0.5588*
	(0.0839)	(0.2978)	(0.0221)	(0.0152)	(0.3852)	(0.3068)
5 years before AI investment	-0.1299*	-0.1129	0.0130	-0.0060	-0.4774	-0.3300
	(0.0730)	(0.2390)	(0.0217)	(0.0164)	(0.3668)	(0.3325)
4 years before AI investment	-0.1047	-0.2558	0.0257	0.0081	-0.2019	-0.0347
	(0.1790)	(0.2446)	(0.0227)	(0.0182)	(0.4670)	(0.4168)
3 years before AI investment	0.0219	-0.1915	0.0115	-0.0034	-0.4115	-0.2503
	(0.0974)	(0.2883)	(0.0200)	(0.0146)	(0.2733)	(0.2596)
2 years before AI investment	-0.1006	-0.3746	-0.0097	-0.0090	0.0857	0.0789
	(0.0921)	(0.3743)	(0.0124)	(0.0128)	(0.2224)	(0.2098)
1 year before AI investment			*Omitted*			
Year of AI investment	0.4176	0.0706	0.0108	0.0146	-1.528***	-0.0067
	(0.2737)	(0.1241)	(0.0194)	(0.0142)	(0.3488)	(0.2554)
1 year after AI investment	0.2026	0.6081*	0.0191	0.0267*	0.4579	0.6726*
	(0.2688)	(0.3658)	(0.0155)	(0.0148)	(0.3974)	(0.3983)
2 years after AI investment	0.0630	0.5425*	0.0224	0.0413**	0.8848	1.166**
	(0.0998)	(0.2905)	(0.0181)	(0.0201)	(0.5691)	(0.5690)
3 years after AI investment	-0.0730	0.4435	0.0382**	0.0500**	0.3900	0.9748*
	(0.0918)	(0.3172)	(0.0157)	(0.0204)	(0.4961)	(0.5402)
4 years after AI investment	0.0930	0.6912*	0.0431**	0.0365	0.2171	1.054
	(0.1537)	(0.3809)	(0.0214)	(0.0221)	(0.6363)	(0.6543)
Firm Size		-0.1537		-0.0019		-0.8740*
		(0.1052)		(0.0186)		(0.5208)
Fixed-effects						
Firm	No	Yes	No	Yes	No	Yes
Year	No	Yes	No	Yes	No	Yes
Fit statistics						
Observations	1,308	1,308	1,308	1,308	1,308	1,308
R^2	0.00238	0.13048	0.01408	0.58070	0.11764	0.66341
Within R^2		0.00173		0.02711		0.06510

Standard errors are clustered by firms
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6. Regression Results of ROE, ROA and Tobin's Q

4.2. Additional Robustness Check

4.2.1. Outliers

Since this study uses financial ratios as dependent variables, we are concerned that significant results may be driven by extreme values, as demonstrated by the numerous outliers in *Figure 5*.

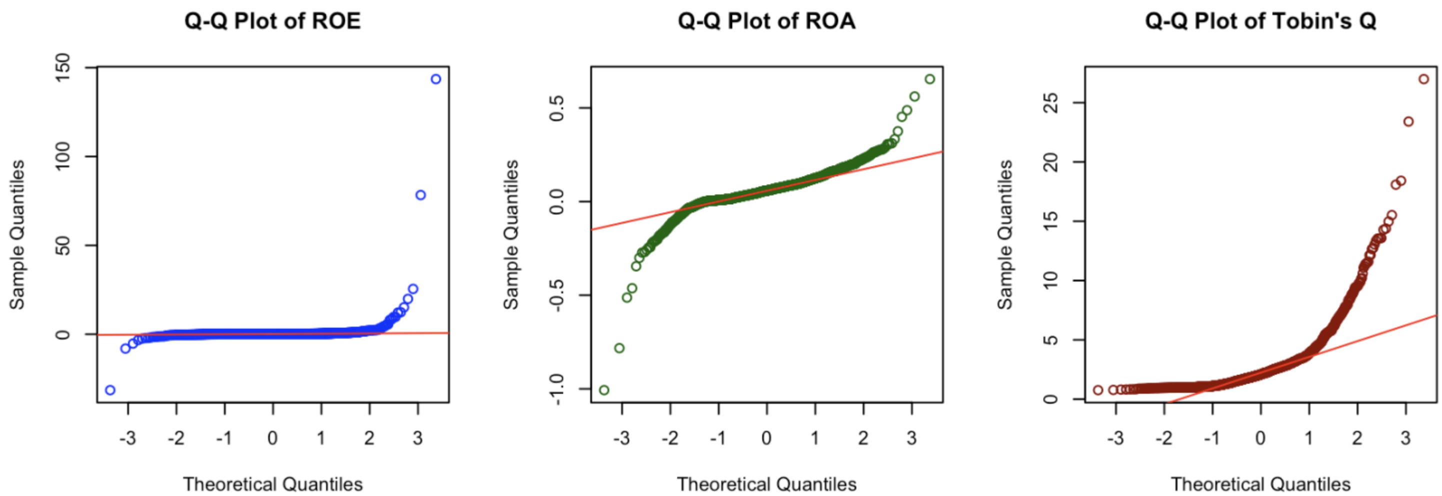

Figure 5. Q-Q Plots of ROE, ROA and Tobin's Q

Hence, we apply winsorisation to handle outliers in three dependent variables as the outliers may lower the robustness of the regression results. Alternatively, the outliers can be removed entirely to make the distribution less skewed. Yet, these extreme observations do not reflect data entry or measurement errors in the context of our study. On the contrary, they reflect the variability in financial ratios and are potentially important observations. Winsorisation allows us to retain these observations and preserve both the sample size and the structure of the dataset, which is essential for reliable statistical inference (Kennedy et al., 1992). Thus, we consider winsorisation the most suitable method to mitigate outliers. Specifically, we winsorise ROE, ROA and Tobin's Q at the 1st and 99th percentiles. The distribution of these variables after winsorisation is displayed in *Figure 6* and the regression results are reported in *Table 7*.

Figure 6. Q-Q Plots of ROE, ROA and Tobin's Q after Winsorisation

According to *Table 7*, we note that after winsorisation, there are some violations of the parallel trend at five years and later pre-investment. However, these differences lose statistical significance thereafter, suggesting that they are not a major concern for our analysis. Across three models, the first year after the AI investment year has positive yet statistically insignificant coefficients with 0.0778 in ROE, 0.0136 in ROA and 0.5693 in Tobin's Q. Therefore, Hypothesis 1 and Hypothesis 3 are not supported.

Notably, ROE's coefficients lack statistical significance post-investment while the coefficients' magnitude of ROA and Tobin's Q are lower but not significantly driven by outliers. The coefficients of ROE in the year of investment and one year after that experience a major change compared to the main results, with a reduction of 0.4306 and 0.1248, respectively. These findings suggest that the earlier positive signal may have been driven by a few observations with exceptionally high ROE. Hence, there is no support for Hypothesis 2 for ROE.

ROA is 0.0263 ($p < 0.1$) in year two and 0.0321 ($p < 0.05$) in year three whereas Tobin's Q is 0.9286 ($p < 0.05$) in year two and 0.8069 ($p < 0.1$) in year three. These results partially support Hypotheses 2 (except ROE) and Hypothesis 4.

Dependent Variables:	ROE	ROA	TOBIN
Model:	(1)	(2)	(3)
Variables			
6+ years before AI investment	-0.2092**	-0.0075	-0.5447*
	(0.0922)	(0.0120)	(0.3076)
5 years before AI investment	-0.1546*	-0.0216*	-0.4529
	(0.0808)	(0.0112)	(0.2792)
4 years before AI investment	-0.0627	-0.0084	-0.3038
	(0.1333)	(0.0129)	(0.2629)
3 years before AI investment	-0.0278	-0.0097	-0.2714
	(0.0942)	(0.0101)	(0.2515)
2 years before AI investment	-0.1278	-0.0032	0.0586
	(0.0915)	(0.0070)	(0.1988)
1 year before AI investment		Omitted	
Year of AI investment	-0.0130	0.0011	-0.0289
	(0.0691)	(0.0081)	(0.2451)
1 year after AI investment	0.0778	0.0136	0.5693
	(0.1208)	(0.0099)	(0.3520)
2 years after AI investment	0.1472	0.0263*	0.9286**
	(0.1072)	(0.0153)	(0.4609)
3 years after AI investment	0.0161	0.0321**	0.8069*
	(0.1000)	(0.0160)	(0.4675)
4 years after AI investment	0.1705	0.0186	0.7103
	(0.1533)	(0.0174)	(0.4973)
Firm Size	-0.0713	-0.0051	-0.7882**
	(0.0479)	(0.0115)	(0.3500)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	1,308	1,308	1,308
R^2	0.50366	0.60850	0.71863
Within R^2	0.01622	0.02612	0.07459

Standard-errors in parentheses are clustered by firms
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7. Regression Results of ROE, ROA and Tobin's Q after Winsorisation

Although having stated that removing outliers is not a suitable method in the case of financial ratios, we conduct an additional test to observe whether the effects of these variables change when outliers are removing completely. We trim the outliers at the same 1st and 99th percentiles as winsorisation, resulting in a reduction to 1,228 firm-year observations. From the regression results in *Table 8*, we see a similar pattern as in winsorisation results with some minor violations at year five and later. Despite being insignificant, ROE's coefficients show positive effects in year one, year two and year four but a negative effect in year three, rejecting Hypothesis 1 and Hypothesis 2 for ROE.

Notably, when looking at ROA and Tobin's Q, their coefficients show significance at the 10% level only in the first-year post-investment and the magnitude of all coefficients are slightly lower than ones in the main results but remain positive. Thus, the findings reject Hypothesis 1 and Hypothesis 3 but partially support Hypothesis 2 (except ROE) and Hypothesis 4.

Dependent Variables:	ROE	ROA	TOBIN
Model:	(1)	(2)	(3)
Variables			
6+ years before AI investment	-0.1424*	-0.0045	-0.5465**
	(0.0736)	(0.0115)	(0.2546)
5 years before AI investment	-0.1089**	-0.0198*	-0.4646**
	(0.0548)	(0.0108)	(0.2055)
4 years before AI investment	0.0270	0.0015	-0.2542
	(0.0901)	(0.0090)	(0.2009)
3 years before AI investment	0.0024	-0.0021	-0.1849
	(0.0648)	(0.0084)	(0.1926)
2 years before AI investment	-0.0550	0.0021	0.0116
	(0.0609)	(0.0062)	(0.1769)
1 year before AI investment		Omitted	
Year of AI investment	0.0139	0.0071	-0.0166
	(0.0471)	(0.0074)	(0.1851)
1 year after AI investment	0.0323	0.0165*	0.5226*
	(0.0445)	(0.0095)	(0.2749)
2 years after AI investment	0.1298	0.0148	0.2273
	(0.0834)	(0.0135)	(0.2651)
3 years after AI investment	-0.0214	0.0170	0.1660
	(0.0590)	(0.0129)	(0.2854)
4 years after AI investment	0.0168	0.0084	0.1328
	(0.0553)	(0.0153)	(0.3356)
Firm Size	-0.0639*	-0.0028	-0.7271***
	(0.0329)	(0.0080)	(0.1590)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	1,228	1,228	1,228
R^2	0.60151	0.64246	0.77308
Within R^2	0.02723	0.02112	0.09159

Standard-errors in parentheses are clustered by firms
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 8. Regression Results of ROE, ROA and Tobin's Q after Outliers Removal

4.2.2. Alternative Estimators

Although popular for its simplicity, the TWFE estimator has some limitations in staggered DID settings since several research suggest that TWFE can produce biased and misleading results when treatment effects vary across units or over time. Instead of analysing all units at a time, recent studies group observational units that have the same initial treatment time period into one cohort when designing a DID study design with multiple treatment periods (Callaway & San't Anna, 2021; Sun & Abraham, 2021).

Goodman-Bacon (2021) and Callaway & Sant'Anna (2021) criticise static TWFE specifications that their estimates may not accurately reflect the average post-treatment effect, thereby likely leading to misleading interpretations. Nonetheless, their studies focus on specifications with a single treatment indicator instead of multiple treatments at multiple periods.

Sun & Abraham (2021) extend this direction to the limitation of dynamic TWFE models. In DID models using TWFE, the estimated coefficients on relative time indicators are interpreted as dynamic effects. However, they are generally weighted average treatment effects from multiple cohorts and time periods and these weights can be contaminated from other periods and groups, especially when treatment effect is heterogeneous (Sun & Abraham, 2021). Therefore, to address these concerns and improve the robustness of our estimates, we re-estimate our models using the estimators developed by Callaway & Sant'Anna (2021) and Sun & Abraham (2021).

The Callaway & Sant'Anna's method estimates treatment effects separately for each group of units that receive treatment in the same period at each point in calendar time and the last period in which the treatment group is treated is used as a baseline time period (Callaway & Sant'Anna, 2021). We use the "did" package in R to run our models using Callaway & Sant' Anna's estimator. However, one issue with the "did" package is that if any treatment group has fewer observations than the number of covariates, the estimation cannot be run (Callaway, 2024). Hence, we must select either dropping the firm size or converting our dataset into balanced panel.

Due to the theoretical and empirical importance of firm size in explaining the relationship of AI investment to firms, we decide to convert the data to a balanced panel, which results in a drop of 14 observations when running the regression. This approach allows us to retain the control variable and minimise data loss. *Table 9* shows the regression results of our specifications using the estimator of Callaway and Sant' Anna. From the results, we find that none of the models have pre-treatment trends, supporting the parallel trend assumption. All estimates are consistent with the main results but lack statistical significance. Especially, coefficients of ROE since year three post-investment are much larger than ones in the main results. In theory, all hypotheses are rejected.

However, since the direction and pattern of all coefficients remain consistent with the main findings, the positive effects may still be present.

DV: Model:	ROE (1)	ROA (2)	Tobin's Q (3)
Variables			
9 years before AI investment	0.0138	0.0153	0.3023
	(0.0454)	(0.0070)	(0.1507)
8 years before AI investment	0.0691	-0.0304	0.0223
	(0.0831)	(0.0239)	(0.4184)
7 years before AI investment	-0.2996	0.0279	0.0980
	(0.3035)	(0.0520)	(0.1891)
6 years before AI investment	-0.9119	0.0084	-0.5093
	(1.4997)	(0.0301)	(0.3499)
5 years before AI investment	0.4844	-0.0044	0.2127
	(0.7108)	(0.0156)	(0.3330)
4 years before AI investment	-0.3419	0.0089	0.1327
	(0.3827)	(0.0195)	(0.2131)
3 years before AI investment	0.4617	-0.0135	-0.2119
	(0.7124)	(0.0178)	(0.4695)
2 years before AI investment	-0.1924	0.0072	0.4618
	(0.3319)	(0.0104)	(0.2616)
1 year before AI investment	0.3649	-0.0146	-0.0468
	(0.6650)	(0.0200)	(0.2444)
Year of AI investment	0.0690	0.0272	-0.0620
	(0.1622)	(0.0165)	(0.3419)
1 year after AI investment	0.7478	0.0449	0.8356
	(0.4914)	(0.0198)	(0.5994)
2 years after AI investment	0.8929	0.0448	1.9761
	(0.7316)	(0.0234)	(1.0357)
3 years after AI investment	2.4932	0.0409	1.0736
	(2.7366)	(0.0177)	(0.5315)
4 years after AI investment	3.2484	0.0342	0.4710
	(3.2780)	(0.0233)	(0.5207)
5 years after AI investment	0.5268	0.0400	0.7530
	(0.4575)	(0.0268)	(0.9109)
Fit statistics			
Observations	1,294	1,294	1,294

Standard errors are clustered by firms
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 9. Regression Results of ROE, ROA, and Tobin's Q using Callaway & Sant' Anna (2021) Estimator

We next assess the dynamic effects of AI investment using the method proposed by Sun & Abraham (2021), which estimates treatment effects by interacting each group of units treated in the same period with relative time indicators. The estimator is implemented by using “fixest” package in R (Berge, 2021). As shown in *Table 10,* we find consistent post-investment improvements in firm performance across ROE, ROA, and Tobin’s Q. ROE rises significantly in the first year after AI investment by 0.8350 ($p < 0.10$), which rejects Hypothesis 1. The positive effect continues in the second year (0.8860, $p < 0.10$) and the following years. However, since the third year after the AI investment year, the effects of ROE lack statistical significance while the magnitude and direction of coefficients remain consistent with the main results, partially supporting Hypothesis 2.

Similarly, ROA’s coefficients are consistent with the main results, its coefficients are positive in year one (0.0263, $p < 0.10$), year two (0.0408, $p < 0.1$) and year three (0.0496, $p < 0.05$), rejecting Hypothesis 1 and completely supporting Hypothesis 2. Whereas Tobin’s Q shows no significant movement in the first year, but an increase of 1.180 in year two ($p < 0.05$) and 0.9092 in year three ($p < 0.1$). Consistent with findings in the main results, the coefficients of ROA and Tobin’s Q lack statistical significance since year four but remain positive. Hence, the results reject Hypothesis 1 and Hypothesis 3 but partially support Hypothesis 2 and Hypothesis 4, aligning with our main findings. Regarding pre-treatment trends, we detect a minor violation for Tobin’s Q in year three before AI investment, indicated by a weekly significant negative coefficient. However, this should not be a concern as this effect disappear afterward.

Dependent Variables:	ROE	ROA	TOBIN
Model:	(1)	(2)	(3)
Variables			
10 years before AI investment	0.0730	0.0729***	0.5505
	(0.1130)	(0.0190)	(0.5343)
9 years before AI investment	0.0082	0.0202	-1.264**
	(0.1805)	(0.0259)	(0.5751)
8 years before AI investment	-0.0400	-0.0034	-0.9577**
	(0.1803)	(0.0155)	(0.4608)
7 years before AI investment	-0.3300	-0.0064	-0.6857*
	(0.2189)	(0.0229)	(0.4097)
6 years before AI investment	-0.4169	-0.0009	-0.6561**
	(0.7834)	(0.0151)	(0.3003)
5 years before AI investment	0.0693	-0.0079	-0.5034
	(0.3077)	(0.0147)	(0.3234)
4 years before AI investment	-0.2322	0.0070	-0.2218
	(0.2131)	(0.0171)	(0.4040)
3 years before AI investment	-0.2544	-0.0038	-0.4168*
	(0.4381)	(0.0133)	(0.2507)
2 years before AI investment	-0.5606	-0.0081	0.0558
	(0.6052)	(0.0119)	(0.2021)
1 year before AI investment		*Omitted*	
Year of AI investment	0.1163	0.0144	-0.1780
	(0.1200)	(0.0135)	(0.2438)
1 year after AI investment	0.8350*	0.0263*	0.5275
	(0.4660)	(0.0149)	(0.3747)
2 years after AI investment	0.8860*	0.0408*	1.180**
	(0.5315)	(0.0215)	(0.5307)
3 years after AI investment	0.8352	0.0496**	0.9092*
	(0.6295)	(0.0219)	(0.4620)
4 years after AI investment	1.287	0.0260	0.3918
	(0.7861)	(0.0222)	(0.4537)
5 years after AI investment	0.4449	0.0306	0.9732
	(0.3969)	(0.0269)	(0.7847)
Firm Size	-0.1530	-0.0000	-0.8862*
	(0.0983)	(0.0186)	(0.5068)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	1,308	1,308	1,308
R^2	0.14042	0.60624	0.68402
Within R^2	0.01315	0.08636	0.12233

Standard-errors in parentheses are clustered by firms
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10. Results of ROE, ROA, and Tobin's Q using Sun & Abraham (2021) Estimator

4.2.3. Matching AI Investors to Non-AI Investors

Another issue with our baseline models is the use of random selection to construct the control group. As randomisation is not possible in the staggered DID research design, it may introduce selection bias into our estimates even though we control for firm size and firm fixed effects. As a result, we decide to match AI-investing firms in the S&P Kensho AI Enablers & Adopters Index to non-AI firms in the S&P 500 Index based on firm size and industry classification (Compustat item GIND) to address this concern. In this robustness check, we employ the optimal full matching as this matching method minimises covariate distance and makes use of as many observations as possible without removing unmatched observations unnecessarily, thereby retaining all AI-investing firms (Hansen, 2004; Ho et al., 2011). The list of matching firms is shown in *Appendix E*.

The optimal full matching method is implemented via the "matchit" package in R (Ho et al., 2011), which utilises functions from the "optmatch" package (Hansen & Klopfer, 2006). The final matched sample includes 145 firms in the control group, resulting in a total of 2,172 firm-year observations. *Table 11* displays the mean differences of ROE, ROA and Tobin's Q between firms that invested in AI and those did not.

Variable	AI-Investing Firms	Non-AI Firms
ROE	0.201	0.38
ROA	0.0651	0.0672
Tobin's Q	3.62	3.04

Table 11. Mean Differences of ROE, ROA, and Tobin's Q between AI-Investing Firms & Non-AI Firms

From the regression results in *Table 12*, the robustness check using optimal full matching to match AI-investing firms to non-AI firms yields consistent results with the baseline analysis. We note that none of the pre-treatment coefficients are statistically significant, supporting parallel trend assumption. Interestingly, while the other two variables remain consistent with the main results, the estimate of ROE in the first year after AI investment are negative at -0.0337 despite not being statistically significant.

All three models show consistent positive effects from year two onwards, but only ROA's estimates in year two and year three are statistically significant at the 10% level and 5% level, respectively, supporting Hypothesis 2 for ROA. Although all coefficients of Tobin's Q show no statistical significance, rejecting Hypothesis 3 and Hypothesis 4, their positive effects since the first year post-investment align with the main results.

Dependent Variables:	ROE	ROA	TOBIN
Model:	(1)	(2)	(3)
Variables			
6+ years before AI investment	0.1296	0.0144	0.2066
	(0.3931)	(0.0150)	(0.3660)
5 years before AI investment	0.1599	0.0054	0.2177
	(0.3668)	(0.0171)	(0.4007)
4 years before AI investment	0.1204	0.0136	0.4066
	(0.3101)	(0.0182)	(0.4820)
3 years before AI investment	-0.1121	0.0010	0.0746
	(0.2707)	(0.0141)	(0.2891)
2 years before AI investment	0.0186	-0.0058	0.2530
	(0.1937)	(0.0124)	(0.2133)
Year of AI investment	-0.2614	0.0099	-0.1397
	(0.2573)	(0.0145)	(0.2421)
1 year after AI investment	-0.0337	0.0203	0.3595
	(0.4043)	(0.0156)	(0.3801)
2 years after AI investment	0.3048	0.0337*	0.6661
	(0.3468)	(0.0201)	(0.5366)
3 years after AI investment	0.2642	0.0423**	0.4400
	(0.3910)	(0.0198)	(0.4780)
4 years after AI investment	0.4892	0.0268	0.5081
	(0.4743)	(0.0200)	(0.5815)
Firm Size	-0.5422	-0.0052	-0.9387**
	(0.7857)	(0.0130)	(0.3988)
Fixed-effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	2,172	2,172	2,172
R^2	0.09521	0.58091	0.69128
Within R^2	0.00066	0.01280	0.04867

Standard-errors in parentheses are clustered by firms
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 12. Results of ROE, ROA, and Tobin's Q using PSM

5. Discussion

This thesis investigates the dynamic impact of AI investment on firm performance and market valuation. In contrast to prior studies that primarily emphasize static average effects, this research focuses on how the impact of AI investment evolves over time. The dependent variables are firm performance and firm market value. The independent variable is AI investment captured by text extraction and textual analysis using an LLM. The analysis of the independent variable AI investment is based is represented through accounting-based indicators – ROE and ROA, whereas firm market value is represented through market-based indicator – Tobin's Q.

The population of this study concentrates on U.S. listed firms included in the S&P Kensho AI Enablers & Adopters Index and the S&P 500 Index, covering a ten-year period from 2013 to 2023. Four hypotheses are developed and empirically tested to address the core research questions. Additionally, to address the concerns regarding the impact of AI investments on firm performance and market value, we employ winsorisation, alternative estimators, and an optimal full matching method. Through these robustness checks, we find the results of ROA the most robust while results of Tobin's Q are positive but show variations in significance level. On the other hand, the results of ROE fluctuate in both direction and magnitude, making ROE less conclusive for the dynamic impact of AI investment on firm performance.

In addressing the research questions at the beginning of this study:

1. ***When does AI investment payoff?***
2. ***Do the short-term effects of AI investment on firms differ from its long-term effects?***

Our empirical results show that firms begin to see payoffs from AI investment in the first year after its initial year of implementation. Although being positive in both short-term and long-term, the effects are stronger in the long term, especially in the second and third period post-investment. Specifically, we observe similar results for both financial performance and market value. Firms having AI investment experience immediate and sustained improvements in both measurements. Additionally, the effects become stronger when we control firm size, firm fixed-effects and year fixed-effects.

By applying staggered DID specification with multi-treatment and relative time framework, we find these effects are visible within the first year following AI investment. Even though the evidence is not strong, the consistency in effect direction across models is contrary to our initial hypotheses that firms often take on additional or unexpected costs due to upgrades, trainings and latency in the early stage of implementation (Doshi et al., 2021; Lui et al., 2022).

Our regression results show two directions in relation to prior research: one differs and the other aligns. First, we observe positive short-term effects of firm performance of AI investment, which contrasts with the Productivity Paradox (Brynjolfsson, 1993) and earlier IT studies (Bae & Kim, 2003) and more recent AI-focused research (Babina et al., 2024; Kim et al., 2022; Lee et al., 2022; Reinking et al., 2015; Sun & Jiao, 2024) that suggest delayed or insignificant impacts of AI investment on firm gains in the short term.

The empirical findings challenge this view by suggesting a distinctive feature in AI compared to previous waves of other technologies. Indeed, the Dynamic Capabilities theory (Teece et al., 1997) can help explain this phenomenon. In this theory, Teece et al. (1997) define a dynamic concept called learned skills in the organizational and managerial processes. This implies that firms have accumulated capabilities, allowing them to exploit value from AI faster than from older technologies (Teece et al., 1997). Hence, the benefits become visible earlier perhaps due to the experience with the past technologies' implementation, explaining why our results present immediate positive effects of AI investment.

Similarly, firm market value shows positive short-term effects, which differs from the literature that suggests negative short-term impacts on firm value after disclosing their AI investments (Babina et al., 2024; Lui et al., 2022; Khallaf et al., 2017). A possible explanation for this effect can be interpreted through the Signalling theory, which was developed by Spence (1978). This theory explains how one party coveys the information to another in order to reduce information asymmetry and influence their behaviours in a favourable direction (Connelly et al., 2010). For a signal to be effective, it must be observable, costly to imitate and linked to the firm's future performance. In the context of AI investment, firms signal their strategic decisions to investors by disclosing AI investments in their annual reports. In addition, AI investment is costly and demanding, meaning only firms with sufficient capabilities can engage in such initiatives, making it associated with firms ‘competitiveness. Thus, since the investors respond positively, firm market value rises in the short term.

Regarding the long-term effects, we observe that the gains persist over time, aligning with our hypotheses and previous studies suggesting the benefits from AI investment will be realised in the later phases (Bae & Kim, 2003; Khallaf et al., 2017; Lee et al., 2022). Our literature review highlights that some empirical studies have found evidence of AI’s positive long-term impact on firms, primarily due to its capabilities in prediction and automation (Agrawal et al., 2022; Huang & Lin, 2025; Kim et al., 2022; Wamba-Taguimdje et al., 2020). We find that the effects appear to be stronger than year one after investment, the effects are highest in year two for firm market value and around year two and year three for financial performance.

These significant positive impacts of AI investment on both performance and market value of firms align with theoretical perspectives. In addition, the results align with the empirical findings of Sun & Jiao (2024), that suggest the maximum performance benefits of market value and accounting value take approximately two years to be realised. Indeed, the Resource-Based View theory supports this direction as it implies that when technology capabilities, in this context are AI capabilities, are practiced and evolved within firms, they will bring long-term values (Barney, 1991).

The number of studies on AI’s impact at firm-level have been rising dramatically in recent years. However, prior research concentrates on the average static effects of post AI investment of publicly listed firms in the U.S. This paper makes three contributions. First, this research adds the first insight into the dynamic effects of the investment in AI on firm outcomes. Our study concentrates on the changes in firm performance and market value four years and onward relative to the initial date provides empirical findings with insights into the current literature by discovering the realised benefits from the investment are immediate and sustained over time. In addition, by exploiting the staggered DID specifications, our study enhances the robustness of this causal interpretation. Regarding the short-term positive effects, the empirical results provide an interesting opportunity for further research to explore how AI investment may follow a different pattern in terms of the early realization of business values. Further, whereas many papers suggest the positive long-term impacts of AI investment (Babina et al., 2024; Huang & Lin, 2025; Kassa et al., 2022; Sun & Jiao, 2024), they offer limited empirical evidence. Our study contributes to the existing literature by providing empirical findings that support this direction and further exploration.

Second, regarding managerial implications, our findings provide empirical support that AI can bring values to firm in both short and long term and become a competitive advantage. The empirical results can serve as evidence for a long-term strategic roadmap, allowing firms's owners and managers to explain the rationale of implementing AI for both institutional and activist investors. However, business leaders and executives should view the investment in AI as a critical long-term strategic choice and carefully evaluate its pros and cons instead of imitating the strategy of AI investment without a systematic plan.

Finally, for investors and stakeholders, the valuable information from this study offers them guidance in decision making and portfolio adjustment. In addition, the findings provide a broad understanding of when financial returns from AI investment are at peak, assisting the stakeholders in anticipating the timing of performance gains associated for long-term growth and market leadership.

6. Limitations & Conclusion

Despite our effort to make the study more robust, it is subject to several limitations that need to be addressed in future research. As discussed, we rely on the date provided in the S&P Kensho AI Enablers & Adopters Index as a proxy for the timing of AI investment. Although we take additional steps to validate this timing such as applying text extraction and textual analysis of firms' 10-K and 20-F filings using LLMs, these methods may still not capture the precise year in which AI investment began. As a result, the intervention date may not fully reflect the true initiation of AI-related activities. Further research can employ alternative method to verify the exact date of firms' AI investment.

Second, the sample size limits the generalisability of our findings regarding the effect of AI investment on firm performance and market value. AI-investing firms are retrieved from the S&P Kensho AI Enablers & Adopters Index, making it less generalised as they operate in the U.S. market. Although our approach to measuring AI investment yields 1,308 firm-year observations, we limit the sample period to the years 2013 through 2023. This restriction reflects our view that AI implementation prior to this timeframe was not fully developed to produce meaningful or comparable firm-level impacts. Additionally, to improve comparability between the treatment and control groups, we exclude firms with small and mid-cap market capitalisations. This reduces the scope of our analysis to measure the dynamic impact of AI investments for firms within these segments.

Third, although our findings are significant across all models and robustness checks, some of the effects are only significant at 10% level. This means these results should be interpreted carefully as an initial indication even though they are consistent in direction. Future research with larger sample size or alternative methods can help confirm our findings.

Fourth, our paper does not explore how the effect may differ across different industries and different firm sizes since AI are applied differently depending on the industry and firms' capabilities. Industry characteristics and firm size can act as moderators or even mediators in the relationship between AI investment and firm outcomes. However, in this study we concentrate primarily on the relationship of AI and firm. Thus, future research can investigate these roles to better understand how industry-specific features and firm size adjust the magnitude of AI's impact.

Finally, the study does not control for industries and variation in AI investment costs, such as investments in infrastructure, technological capabilities, or employee training, which may also influence post-investment outcomes. These underlying cost structures could influence the timeline and magnitude of performance improvements. Without controlling for these firm-specific investments, it is difficult to disentangle whether observed outcomes reflect the strategic value of AI itself, or the broader resource commitments required to implement it effectively. In addition, although we apply optimal full matching method, firm and year fixed effects, and control for firm size to minimize selection bias, there may still be omitted variables that can impact the relationship of AI investment and firm outcomes. Future research could enhance the robustness of these findings by including costs, industry differences, and using alternative method to better isolate the causal impact of AI investment.

In conclusion, this study examines how AI investment affects firm performance and market value over time with a focus on publicly listed firms in the U.S. market from 2013 to 2023. The results show that AI can bring value to firms both in the short and long term, with the strongest effects showing up around the second and third years after investment. Furthermore, we find that the gains may appear earlier than expected, which is different from the patterns seen in past technology waves. By using a staggered DID approach with the multi-treatment, relative time framework and additional robustness checks, our study strengthens the causal interpretation of these findings. Overall, the empirical results offer new evidence to support the impact of AI in improving firm performance and market valuation, providing a useful starting point for both future studies and practical decisions around AI investment.

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Appendices

A. Literature Review

Author	Title	Country	Independent Variable	Dependent Variable
Babina et al. (2024)	Artificial intelligence, firm growth, and product innovation	US	AI investments	Firm growth
Cao et al. (2021)	Understanding managers' attitudes and behavioural intentions towards using artificial intelligence for organizational decision-making	UK	Perceived expectancy, threat and concern towards AI	Intention to use AI
Chen et al. (2023)	The role of artificial intelligence in effective business operations during COVID-19	China	AI	Managers' satisfaction & firm performance
Cheng et al. (2025)	Internal business process governance and external regulation: How does AI technology empower financial performance?	China	AI technology	Firm financial performance
Dong et al. (2025)	Growing up in the modern world: how does artificial intelligence enhance firm growth?	US	AI	Firm growth
Huang & Lin (2025)	Firm Performance on Artificial Intelligence Implementation	US	AI implementations	Firm financial performance, productivity, and market value
Kassa et al. (2025)	The impact of artificial intelligence on organizational performance: The mediating role of employee productivity	Ethiopia	AI capabilities	Firm performance
Kim et al. (2022)	The Impact of Artificial Intelligence on Firm Performance	US	AI investments	Firm performance

Lee et al. (2022)	When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy	South Korea	AI-adoption intensity	Firm performance
Li et al. (2024)	Tech for stronger financial market performance: the impact of AI on stock price crash risk in emerging market	China	AI investment	Stock price crash risk
Liu et al. (2025)	Promoting or inhibiting: The impact of artificial intelligence application on corporate environmental performance	China	AI application	Corporate environmental performance
Lui et al. (2022)	Impact of artificial intelligence investment on firm value	US	AI investment announcement	Firm value
Mishra et al. (2022)	Artificial intelligence focuses and firm performance	US	AI focus	Firm financial performance
Schreieck et al. (2024)	The Effect of Digital Platform Strategies on Firm Value in the Banking Industry	41 countries	Announcement of digital platform strategy (including AI)	Cumulative abnormal stock returns
Sharma & Kumar (2024)	Enablers Driving Success of Artificial Intelligence in Business Performance: A TISM-MICMAC Approach	Not mentioned	Firm resilience, tech-enabled manpower, digital platform and intelligence process automation	Quality management, customer satisfaction, firm value, operational efficiency and financial performance
Song et al. (2025)	Are companies better off with AI? The effect of AI service failure events on firm value	US	AI service failure events	Firm market value

Sullivan & Wamba (2024)	Artificial intelligence and adaptive response to market changes: A strategy to enhance firm performance and innovation	UK & France	AI-enabled capabilities	Adaptive response to market changes, firm performance and innovation
Sun & Jiao (2024)	Emerging IT investments and firm performance: a perspective of the digital options	China	Emerging IT Investments (AI, Blockchain, Cloud Computing, Big Data, Internet of Things)	Firm Performance
Wamba-Taguimdje et al. (2020)	Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects	Not mentioned	AI-based transformation projects	Firm performance

B. List of Firms Modified in the Dataset

Ticker	Action	Rationale
FB	Changed and merged to META	The ticker symbol was changed from FB to META in 2012.
GOOG	Removed	GOOG and GOOGL are from the same entity. Hence, we keep GOOGL and remove GOOG.
FCAU	Changed and merged to STLA	The ticker symbol was changed from FCAU to STLA in 2021.
CACI	Removed	Market capitalization is lower than $15B
RNG	Removed	Market capitalization is lower than $15B
NICE	Removed	Market capitalization is lower than $15B
DDD	Removed	Market capitalization is lower than $15B
LPSN	Removed	Market capitalization is lower than $15B
AMBA	Removed	Market capitalization is lower than $15B
SLP	Removed	Market capitalization is lower than $15B
EGHT	Removed	Market capitalization is lower than $15B
AUDC	Removed	Market capitalization is lower than $15B

C. Relative Time Dummies before and after Collapsing

REL_TIME	-10	-9	−8	−7	−6	−5	−4	−3	−2	−1	0	1	2	3	4	5
Before	1	15	18	25	38	55	56	57	59	61	758	59	46	39	31	16
After					97	55	56	57	59	61	758	59	46	39	47	

D. List of Firms in Treatment and Control Group in Main Models

TREATMENT GROUP	
Ticker	**Firm Name**
A	JPMorgan Chase & Co.
ADBE	Apple Inc.
ADSK	ANSYS, Inc.
AI	C3.ai, Inc. Class A
ALTR	Altair Engineering Inc.
AMD	Adobe Inc.
ANSS	Duke Energy Corporation
AVAV	Aerovironment Inc
AVGO	U.S. Bancorp

AZPN	Aspen Technology Inc
BABA	Alibaba Group Holding Ltd ADR
BIDU	Baidu.com ADR
BLKB	Blackbaud Inc
CRL	The Coca-Cola Company
CSCO	Bank of America Corporation
DOV	Dover Corp
EXLS	ExlService Holdings Inc
GD	General Dynamics
GLOB	Globant SA
GOOG	Alphabet Inc C
HON	Honeywell Intl Inc
IBM	Intl Business Machines Corp
INFY	Infosys Limited ADR
ING	Ing Groep NV ADR
INTC	Intel Corp
KBR	KBR Inc
KLAC	KLA Corporation
LC	LendingClub Corp
LSCC	Lattice Semiconductor Co
MA	Mastercard Inc A
MDT	Medtronic plc
MELI	Mercadolibre inc
META	Oracle Corporation
MSFT	Microsoft Corp
NIO	NIO Inc-ADR
NOC	Northrop Grumman Corp
NOW	ServiceNow Inc.
NTAP	NetApp Inc
NTES	NetEase Inc ADR
NVDA	Nvidia Corp
ORCL	Oracle Corp
OTEX	Open Text Corp
PATH	UiPath, Inc.
PSTG	Pure Storage Inc
PTC	PTC Inc
QCOM	QUALCOMM Inc
SAP	SAP SE ADR
SMCI	Super Micro Computer Inc

SNAP	Snap, Inc.
STLA	Stellantis N.V.
STM	STMicroelectronics NV NYShs
STX	Seagate Technology
SYK	Stryker Corp
TDC	Teradata Corp
TM	Toyota Motor Corp ADR
TSLA	Tesla, Inc
VC	Visteon Corp
VMW	VMware Inc A
WB	WEIBO CORP ADR
ZBH	Zimmer Biomet Holdings Inc
ZBRA	Zebra Technologies Corp
CONTROL GROUP	
Ticker	**Firm Name**
AAPL	Applied Materials, Inc.
ABT	The Boeing Company
ACGL	Bank of America Corporation
ACN	BlackRock, Inc.
ADI	Bristol-Myers Squibb Company
ADP	Citigroup Inc.
AIG	Caterpillar Inc.
AKAM	Chubb Limited
AMAT	Colgate-Palmolive Company
BA	The Cooper Companies, Inc.
BAC	Costco Wholesale Corporation
BLK	Salesforce, Inc.
BMY	CSX Corporation
C	CVS Health Corporation
CAT	Chevron Corporation
CB	Dominion Energy, Inc.
CL	Delta Air Lines, Inc.
COO	Deere & Company
COST	Duke Energy Corporation
CRM	FedEx Corporation
CSX	GE Aerospace
CVS	General Mills, Inc.
CVX	The Goldman Sachs Group, Inc.
D	Johnson & Johnson

DAL	JPMorgan Chase & Co.
DE	The Kraft Heinz Company
DUK	Kimberly-Clark Corporation
FDX	The Coca-Cola Company
GE	Lockheed Martin Corporation
GIS	Southwest Airlines Co.
GS	Mondelez International, Inc.
JNJ	MetLife, Inc.
JPM	3M Company
KHC	Merck & Co., Inc.
KMB	NextEra Energy, Inc.
KO	Norfolk Southern Corporation
LMT	PepsiCo, Inc.
LUV	Pfizer Inc.
MDLZ	The Procter & Gamble Company
MET	Prudential Financial, Inc.
MMM	RTX Corporation
MRK	The Southern Company
NEE	AT&T Inc.
NSC	Target Corporation
PEP	T-Mobile US, Inc.
PFE	Union Pacific Corporation
PG	United Parcel Service, Inc.
PRU	U.S. Bancorp
RTX	Verizon Communications Inc.
SO	Walgreens Boots Alliance, Inc.
T	Wells Fargo & Company
TGT	Walmart Inc.
TMUS	Exxon Mobil Corporation
UNP	Union Pacific Corporation
UPS	United Parcel Service, Inc.
USB	U.S. Bancorp
VZ	Verizon Communications Inc.
WBA	Walgreens Boots Alliance, Inc.
WFC	Wells Fargo & Company
WMT	Walmart Inc.
XOM	Exxon Mobil Corporation

E. List of Firms in Treatment and Control Group after Full Optimal Matching

TREATMENT GROUP			
Ticker	**Firm Name**	**GISC Industry Code**	**Industry Name**
AMD	Advanced Micro Devices	453010	Semiconductors & Semiconductor Equipment
HON	Honeywell Intl Inc	201050	Industrial Conglomerates
ADSK	Autodesk Inc	451030	Software
DOV	Dover Corp	201060	Machinery
GD	General Dynamics	201010	Aerospace & Defence
INTC	Intel Corp	453010	Semiconductors & Semiconductor Equipment
IBM	Intl Business Machines Corp	451020	IT Services
KLAC	KLA Corporation	453010	Semiconductors & Semiconductor Equipment
MDT	Medtronic plc	351010	Health Care Equipment & Supplies
NOC	Northrop Grumman Corp	201010	Aerospace & Defence
SYK	Stryker Corp	351010	Health Care Equipment & Supplies
MSFT	Microsoft Corp	451030	Software
ORCL	Oracle Corp	451030	Software
ADBE	Adobe Inc.	451030	Software
ING	Ing Groep NV ADR	401010	Banks
LSCC	Lattice Semiconductor Co	453010	Semiconductors & Semiconductor Equipment
GLOB	Globant SA	451020	IT Services
PTC	PTC Inc	451030	Software
LC	LendingClub Corp	402020	Consumer Finance
TM	Toyota Motor Corp ADR	251020	Automobiles
WB	WEIBO CORP ADR	502030	Interactive Media & Services
BABA	Alibaba Group Holding Ltd ADR	255030	Broadline Retail
CSCO	Cisco Systems Inc	452010	Communications Equipment
ZBRA	Zebra Technologies Corp	452030	Electronic Equipment, Instruments & Components
QCOM	QUALCOMM Inc	453010	Semiconductors & Semiconductor Equipment
PSTG	Pure Storage Inc	452020	Technology Hardware, Storage & Peripherals
SNAP	Snap, Inc.	502030	Interactive Media & Services
AZPN	Aspen Technology Inc	451030	Software
STM	STMicroelectronics NV NYShs	453010	Semiconductors & Semiconductor Equipment
ALTR	Altair Engineering Inc.	451030	Software
NIO	NIO Inc-ADR	251020	Automobiles
AI	C3.ai, Inc. Class A	451030	Software
PATH	UiPath, Inc.	451030	Software

NTAP	NetApp Inc	452020	Technology Hardware, Storage & Peripherals
OTEX	Open Text Corp	451030	Software
ANSS	ANSYS Inc	451030	Software
STLA	Stellantis N.V.	251020	Automobiles
SAP	SAP SE ADR	451030	Software
NVDA	Nvidia Corp	453010	Semiconductors & Semiconductor Equipment
A	Agilent Technologies Inc	352030	Life Sciences Tools & Services
VC	Visteon Corp	251010	Automobile Components
CRL	Charles River Laboratories	352030	Life Sciences Tools & Services
NTES	NetEase Inc ADR	502020	Entertainment
ZBH	Zimmer Biomet Holdings Inc	351010	Health Care Equipment & Supplies
STX	Seagate Technology	452020	Technology Hardware, Storage & Peripherals
MA	Mastercard Inc A	402010	Financial Services
GOOGL	Alphabet Inc C	502030	Interactive Media & Services
EXLS	ExlService Holdings Inc	202020	Professional Services
BIDU	Baidu.com ADR	502030	Interactive Media & Services
META	Facebook Inc A	502030	Interactive Media & Services
NOW	ServiceNow Inc.	451030	Software
KBR	KBR Inc	202020	Professional Services
AVAV	Aerovironment Inc	201010	Aerospace & Defense
SMCI	Super Micro Computer Inc	452020	Technology Hardware, Storage & Peripherals
MELI	Mercadolibre inc	255030	Broadline Retail
VMW	VMware Inc A	451030	Software
TDC	Teradata Corp	451030	Software
AVGO	Broadcom Inc	453010	Semiconductors & Semiconductor Equipment
TSLA	Tesla, Inc	251020	Automobiles
INFY	Infosys Limited ADR	451020	IT Services
BLKB	Blackbaud Inc	451030	Software
CONTROL GROUP			
Ticker	**Firm Name**	**GICS Industry Code**	**Industry Name**
ABT	Abbott Laboratories	351010	Health Care Equipment & Supplies
SWKS	Skyworks Solutions, Inc.	453010	Semiconductors & Semiconductor Equipment
AXP	American Express Company	402020	Consumer Finance
ADI	Analog Devices, Inc.	453010	Semiconductors & Semiconductor Equipment
AMAT	Applied Materials, Inc.	453010	Semiconductors & Semiconductor Equipment

ADP	Automatic Data Processing, Inc.	202020	Professional Services
BAX	Baxter International Inc.	351010	Health Care Equipment & Supplies
BDX	Becton, Dickinson and Company	351010	Health Care Equipment & Supplies
BA	The Boeing Company	201010	Aerospace & Defence
CAT	Caterpillar Inc.	201060	Machinery
JPM	JPMorgan Chase & Co.	401010	Banks
C	Citigroup Inc.	401010	Banks
COO	The Cooper Companies, Inc.	351010	Health Care Equipment & Supplies
GLW	Corning Incorporated	452030	Electronic Equipment, Instruments & Components
CMI	Cummins Inc.	201060	Machinery
DHR	Danaher Corporation	352030	Life Sciences Tools & Services
DE	Deere & Company	201060	Machinery
DIS	The Walt Disney Company	502020	Entertainment
RVTY	Revvity, Inc.	352030	Life Sciences Tools & Services
EFX	Equifax Inc.	202020	Professional Services
FITB	Fifth Third Bancorp	401010	Banks
RF	Regions Financial Corporation	401010	Banks
MTB	M&T Bank Corporation	401010	Banks
USB	U.S. Bancorp	401010	Banks
F	Ford Motor Company	251020	Automobiles
AJG	Arthur J. Gallagher & Co.	403010	Insurance
GE	GE Aerospace	201010	Aerospace & Defence
GM	General Motors Company	251020	Automobiles
LHX	L3Harris Technologies, Inc.	201010	Aerospace & Defence
HPQ	HP Inc.	452020	Technology Hardware, Storage & Peripherals
HBAN	Huntington Bancshares Incorporated	401010	Banks
ITW	Illinois Tool Works Inc.	201060	Machinery
J	Jacobs Solutions Inc.	202020	Professional Services
LRCX	Lam Research Corporation	453010	Semiconductors & Semiconductor Equipment
LMT	Lockheed Martin Corporation	201010	Aerospace & Defence
MU	Micron Technology, Inc.	453010	Semiconductors & Semiconductor Equipment
MSI	Motorola Solutions, Inc.	452010	Communications Equipment
BAC	Bank of America Corporation	401010	Banks
NDSN	Nordson Corporation	201060	Machinery
WFC	Wells Fargo & Company	401010	Banks

PNC	The PNC Financial Services Group, Inc.	401010	Banks
PCAR	PACCAR Inc	201060	Machinery
PH	Parker-Hannifin Corporation	201060	Machinery
PAYX	Paychex, Inc.	202020	Professional Services
PNR	Pentair plc	201060	Machinery
SNA	Snap-on Incorporated	201060	Machinery
KEY	KeyCorp	401010	Banks
SWK	Stanley Black & Decker, Inc.	201060	Machinery
TFX	Teleflex Incorporated	351010	Health Care Equipment & Supplies
TER	Teradyne, Inc.	453010	Semiconductors & Semiconductor Equipment
TXN	Texas Instruments Incorporated	453010	Semiconductors & Semiconductor Equipment
TXT	Textron Inc.	201010	Aerospace & Defence
TMO	Thermo Fisher Scientific Inc.	352030	Life Sciences Tools & Services
TYL	Tyler Technologies, Inc.	451030	Software
RTX	RTX Corporation	201010	Aerospace & Defence
WST	West Pharmaceutical Services, Inc.	352030	Life Sciences Tools & Services
WDC	Western Digital Corporation	452020	Technology Hardware, Storage & Peripherals
JKHY	Jack Henry & Associates, Inc.	402010	Financial Services
TFC	Truist Financial Corporation	401010	Banks
IT	Gartner, Inc.	451020	IT Services
FI	Fiserv, Inc.	402010	Financial Services
CDNS	Cadence Design Systems, Inc.	451030	Software
FICO	Fair Isaac Corporation	451030	Software
APH	Amphenol Corporation	452030	Electronic Equipment, Instruments & Components
DELL	Dell Technologies Inc.	452020	Technology Hardware, Storage & Peripherals
IEX	IDEX Corporation	201060	Machinery
TECH	Bio-Techne Corporation	352030	Life Sciences Tools & Services
GEN	Gen Digital Inc.	451030	Software
EA	Electronic Arts Inc.	502020	Entertainment
IQV	IQVIA Holdings Inc.	352030	Life Sciences Tools & Services
PAYC	Paycom Software, Inc.	202020	Professional Services
KEYS	Keysight Technologies, Inc.	452030	Electronic Equipment, Instruments & Components
SYF	Synchrony Financial	402020	Consumer Finance
ANET	Arista Networks Inc	452010	Communications Equipment
HOLX	Hologic, Inc.	351010	Health Care Equipment & Supplies

CFG	Citizens Financial Group, Inc.	401010	Banks
TRMB	Trimble Inc.	452030	Electronic Equipment, Instruments & Components
GDDY	GoDaddy Inc.	451020	IT Services
IDXX	IDEXX Laboratories, Inc.	351010	Health Care Equipment & Supplies
PYPL	PayPal Holdings, Inc.	402010	Financial Services
ROP	Roper Technologies, Inc.	451030	Software
SNPS	Synopsys, Inc.	451030	Software
BSX	Boston Scientific Corporation	351010	Health Care Equipment & Supplies
STE	STERIS plc	351010	Health Care Equipment & Supplies
MTCH	Match Group, Inc.	502030	Interactive Media & Services
HPE	Hewlett Packard Enterprise Company	452020	Technology Hardware, Storage & Peripherals
FTV	Fortive Corporation	201060	Machinery
INTU	Intuit Inc.	451030	Software
MCHP	Microchip Technology Incorporated	453010	Semiconductors & Semiconductor Equipment
HWM	Howmet Aerospace Inc.	201010	Aerospace & Defence
JBL	Jabil Inc.	452030	Electronic Equipment, Instruments & Components
CDW	CDW Corporation	452030	Electronic Equipment, Instruments & Components
BWA	BorgWarner Inc.	251010	Automobile Components
IR	Ingersoll Rand Inc.	201060	Machinery
COF	Capital One Financial Corporation	402020	Consumer Finance
RMD	ResMed Inc.	351010	Health Care Equipment & Supplies
CRWD	CrowdStrike Holdings, Inc.	451030	Software
OTIS	Otis Worldwide Corporation	201060	Machinery
PLTR	Palantir Technologies Inc.	451030	Software
GEHC	GE HealthCare Technologies Inc.	351010	Health Care Equipment & Supplies
WAB	Westinghouse Air Brake Technologies Corporation	201060	Machinery
WAT	Waters Corporation	352030	Life Sciences Tools & Services
TTWO	Take-Two Interactive Software, Inc.	502020	Entertainment
QRVO	Qorvo, Inc.	453010	Semiconductors & Semiconductor Equipment
MTD	Mettler-Toledo International Inc.	352030	Life Sciences Tools & Services
VRSN	VeriSign, Inc.	451020	IT Services
CTSH	Cognizant Technology Solutions Corporation	451020	IT Services
EBAY	eBay Inc.	255030	Broadline Retail

APTV	Aptiv PLC	251010	Automobile Components
FFIV	F5, Inc.	452010	Communications Equipment
JNPR	Juniper Networks, Inc.	452010	Communications Equipment
AKAM	Akamai Technologies, Inc.	451020	IT Services
TDY	Teledyne Technologies Incorporated	452030	Electronic Equipment, Instruments & Components
EW	Edwards Lifesciences Corporation	351010	Health Care Equipment & Supplies
ON	ON Semiconductor Corporation	453010	Semiconductors & Semiconductor Equipment
ISRG	Intuitive Surgical, Inc.	351010	Health Care Equipment & Supplies
ALGN	Align Technology, Inc.	351010	Health Care Equipment & Supplies
GPN	Global Payments Inc.	402010	Financial Services
ACN	Accenture plc	451020	IT Services
AXON	Axon Enterprise, Inc.	201010	Aerospace & Defence
NFLX	Netflix, Inc.	502020	Entertainment
TDG	TransDigm Group Incorporated	201010	Aerospace & Defence
CRM	Salesforce, Inc.	451030	Software
MPWR	Monolithic Power Systems, Inc.	453010	Semiconductors & Semiconductor Equipment
DXCM	DexCom, Inc.	351010	Health Care Equipment & Supplies
WBD	Warner Bros. Discovery, Inc.	502020	Entertainment
LDOS	Leidos Holdings, Inc.	202020	Professional Services
LYV	Live Nation Entertainment, Inc.	502020	Entertainment
FIS	Fidelity National Information Services, Inc.	402010	Financial Services
PANW	Palo Alto Networks, Inc.	451030	Software
FSLR	First Solar, Inc.	453010	Semiconductors & Semiconductor Equipment
BR	Broadridge Financial Solutions, Inc.	202020	Professional Services
PODD	Insulet Corporation	351010	Health Care Equipment & Supplies
TEL	TE Connectivity plc	452030	Electronic Equipment, Instruments & Components
DFS	Discover Financial Services	402020	Consumer Finance
V	Visa Inc.	402010	Financial Services
VRSK	Verisk Analytics, Inc.	202020	Professional Services
FTNT	Fortinet, Inc.	451030	Software
CPAY	Corpay, Inc.	402010	Financial Services
NXPI	NXP Semiconductors N.V.	453010	Semiconductors & Semiconductor Equipment
HII	Huntington Ingalls Industries, Inc.	201010	Aerospace & Defence

ENPH	Enphase Energy, Inc.	453010	Semiconductors & Semiconductor Equipment
EPAM	EPAM Systems, Inc.	451020	IT Services
XYL	Xylem Inc.	201060	Machinery