# The Value of AI Innovations in Non-IT Firms*

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February 2025

**Abstract**

As the latest general-purpose-technology (GPT), AI technologies have recently started to diffuse from the general sector (IT industry) to the application sectors of AI (non-IT industries) at scale. To understand the benefits of AI innovations in application sectors, we study the value of AI innovations in non-IT firms. We find that AI innovations are more valuable compared to other innovations in non-IT industries, as AI patents exhibit a 6 percent value premium relative to other patents. These innovations are also associated with future returns, as equal- (capped-value-) weighted portfolios formed on AI patents yield a 32 (19) basis-point alpha per month after adjusting for risk and mispricing factors. Lastly, we find that the innovation spillovers and improvements in the competitive position associated with AI innovations likely explain the AI innovations value premium in non-IT industries, as AI patents are associated with more forward citations, and higher market share of sales.

**Keywords:** Artificial Intelligence, Innovation, Valuation

**JEL Codes:** O31, O32, O33, O34, G12

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# 1 Introduction

Scholars have argued that, throughout economic history, a small set of general-purpose technologies (GPTs), such as steam engines, electricity, computers, and the internet have been at the forefront of driving sustained periods of economic growth (Bresnahan and Trajtenberg, 1995), as these technologies find new applications and diffuse throughout the economy. Thus, when GPTs are first developed, there are substantial economic benefits at stake for society, businesses, and investors. To understand the evolving economic impact of GPTs, in this study, we examine the most recent GPT which is still in development - Artificial Intelligence (AI) technologies, and study the market value of these innovations for the firms that apply and invest in these technologies.

While many commentators have suggested that there are wide-ranging benefits of AI technologies, much like other GPTs before, we conjecture that the value of these technologies varies as the technology develops and matures over time. GPTs are often characterized by long development lags, as the technologies are continuously refined and developed for specific applications (Bresnahan, 2010). In Figure 1, we show that the development of AI follows this characterization, as the patenting of AI technologies is steadily increasing over decades. The gradual development of AI and its applications therefore leads to empirical questions on the value of AI innovations over time and the forces that underpin its value.

Moreover, there are also distinct features of GPTs that motivate an empirical study on the value of these technologies. First, because of the innovation diffusion between the general and application sectors during the development of GPTs (Bresnahan, 2010), AI innovations likely exhibit exceptionally large knowledge spillovers across industries and firms. As shown in Figure 2, we find that patenting activity of AI, which initially started in the Information Technology (IT) sector (or the general sector for AI), has spilled over into multiple application sectors, such as retail and wholesale trade, finance, services, and transportation. These striking patterns thus motivate analyses on the value of AI innovations as they diffuse from general to application sectors.

Against this backdrop, we focus our analysis on the non-IT firms that invest in AI innovations, as AI technologies start to diffuse into their industries.[1] We focus on these industries for two reasons. First, AI innovations in non-IT firms is a more recent phenomenon compared to the development of AI in the IT sector. While AI technologies have already been in development in the IT sector for several decades, these technologies have only just started to be applied and integrated into non-IT firms at scale, with the introduction of big data and deep learning technologies in the early 2010s (LeCun et al, 2015). Second, the valuation of these technologies in non-IT firms is unclear ex ante. Development of these technologies could be more challenging for non-IT firms as it relies on digital capital (Tambe et al, 2020), which is likely less common in non-IT firms. On the other hand, developing applications of AI in non-IT industries also benefits from local industry knowledge (Conti et al, 2019). Hence, the valuation of AI innovations in non-IT industries is an open empirical question.

We begin our study by first examining the profile of non-IT firms that invest in patented AI technologies from 2001 to 2023 that have been identified as such by the US Patent and Trademark Office (USPTO) (Giczy et al, 2022). Over time, we find that an increasingly concentrated group of firms are responsible for AI innovations in non-IT sectors. Specifically, we find that the intensive (extensive) margin of AI patenting is rising (declining) over time (see Figure 3), which indicates a growing concentration in the patenting of AI innovation.[2] Additionally, we investigate the factors that are associated with the *initiation* of AI patenting

[1] We define IT firms as firms operating in the software industry, measured by the SIC Code 737 (Computer Programming, Data Processing, and other Computer Related Services).
[2] The fraction of firms involved with AI patenting peaked at around 7 percent in 2010, and has since fallen to 4 percent in 2023, while the number of AI patents per firm has steadily risen from 10 to 50 from 2001-2023.

activity. Consistent with the idea that complementary knowledge in non-AI technologies and software technologies is important for developing AI innovation in non-IT industries, we find that a 10 percent increase in the prior stock of software patents, and non-AI patents, is associated with a 0.9 and 0.4 percent increase, respectively, in the probability of initiating AI patenting activity. Moreover, we find that firms with lower market share of sales in that industry tend to engage in AI patenting activity for the first time, suggesting that firms may be investing in AI innovations to increase market share. Overall, these results suggest that extensive knowledge in the software and the non-IT domains, as well as the firms' competitive position, are key factors that drive non-IT firms to engage in AI innovations.

Next we study the short-term market assessment of the value of AI innovations as measured by the value of AI patents.[3] As prior work has shown robust evidence that patents create value for firms (Hall et al, 2005; Kogan et al, 2017), we examine whether AI patents are *more* valuable compared to non-AI patents (hereafter referred to as the value premium of AI innovations). Our analysis shows that AI patents are roughly 6 percent more valuable compared to non-AI patents from the same industry and technology class.[4]

As the valuation of innovation could be uncertain for investors (Fitzgerald et al, 2020), we further examine whether AI innovations predict future returns. To test this idea, we form a portfolio of non-IT firms that engage in above median patenting activity and above median share of AI patenting activity over the prior year ("the AI portfolio"), and we find that the equal

[3] We follow prior literature in economics and finance that examines the private economic value of innovation activity through patent values. We expect this value to serve as a lower bound for the societal benefits of AI innovations, which is likely higher due to the knowledge spillovers associated with these technologies.

[4] We note that the value premium that we measure in our analysis is based on the value of patents measured as of the grant date, which means that the market expectations of capitalized innovation costs are already embedded in prices at this point. Furthermore, to address concerns that markets do not fully capitalize expenditures in intangibles, like R&D, we also control for past expenditures on innovation, as measured by R&D intensity and its first and second lags, in our main regression model. Consistent with the notion that capitalization issues play a limited role in driving our results, we show that the inclusion of this control variable has a minimal effect on the economic magnitude of the value premium of AI patents.

(capped-value) weighted returns of this portfolio, exhibit an alpha of 32 and 19 basis-points per month, respectively (or 4 percent and 2 percent, respectively, on an annual basis), after adjusting for the Fama-French 5 factors (Fama and French, 2015), momentum and the mispricing factors in Stambaugh and Yuan (2017). In contrast, the portfolio of non-IT firms that engage in above median patenting activity but below median share of AI patenting activity over the prior year ("the non-AI portfolio"), exhibits statistically insignificant alpha after adjusting for the same factors.

To understand the drivers of the value of AI innovation, we explore two potential explanations. First, we examine the hypothesis that the value of AI innovations is driven by the widespread innovation spillovers that are associated with these technologies. In particular, there are two types of innovation spillovers that likely explain the value of AI innovations - (1) advances in the technical capabilities of core AI technologies that spillover from the IT sector to the non-IT sector and (2) the potential for AI innovation in non-IT firms to spur follow-on innovations. To examine the first source of value from innovation spillovers, we exploit a key breakthrough event in the development of AI technologies that occurred in the computer science domain - AlexNet, and investigate its impact on investor valuation of the downstream AI patents for companies that are more likely to benefit from AI technologies. Our analyses show that high AI potential firms (as measured by the Felten et al, 2021 index on AI exposure) exhibit a 32 percent increase in the value of AI patents after AlexNet, which suggests that technological breakthroughs from computer science research, play a key role in explaining the value of AI innovations in application sectors.

To study the second source of value from innovation spillovers, we assess whether AI innovations are highly influential innovations that spur follow-on innovations. As prior research shows that more influential and highly cited innovations are more valued by investors

(Hall et al, 2005), we hypothesize that the potential of follow-on innovation from AI innovations could also explain the value premium of these innovations. Our analysis finds that AI innovations are highly influential, as AI patents are cited about 30 percent more compared to non-AI patents, and are also cited by other patents in the same technology class by around 10 percent more. In addition, we also find that forward citations are associated with higher patent values in AI patents, which lends further support to the notion that the innovation spillovers from these patents are a source of its value.

Our second hypothesis on the drivers of AI innovations' value, posits that these innovations create value by improving the firm's competitive position through (1) greater efficiencies in the production process (Tambe et al, 2014) and (2) the introduction of new products and services (Babina et al, 2024). To study this channel, we analyze the accounting performance changes of firms that actively engage in AI patenting. Our analysis finds that firms that invest more in AI patents tend to exhibit higher future return-on-sales (ROS) and gross margins. Specifically, our estimates show that a one standard deviation change in the value of AI patents granted in the year, is associated with a 0.3 percent increase in both ROS and gross margins in the following year (or 9 percent and 0.7 percent, relative to the sample average of ROS and gross margin of 3.2 and 39 percent, respectively). In addition, we further find that firms that engage in AI innovations improve their competitive position in the following one to three years. Specifically, a one standard deviation increase in the value of AI patents in the year, is associated with a 0.5 percent increase in sales-based market share in the following year (or 7 percent relative to the sample average of market share of 6.5 percent).

Our findings contribute to several strands of literature. First, we contribute to the literature on the valuation of innovation and patents. Prior work in finance has found consistent evidence that innovation and patenting activities are associated with higher market values for firms (Hall et al, 2005; Kogan et al, 2017), and can drive runups in aggregate stock market value (Nicholas, 2008). Other studies have uncovered key cross-sectional differences in market value of patents (Gao et al, 2018; Hirshleifer et al, 2013; Hirshleifer et al, 2018; Fitzgerald et al, 2020; Stoffman et al, 2022). We contribute to these studies by studying a group of patents that is both new and rising in importance - AI patents. In particular, we find that these patents are more highly valued by investors compared to other patents in non-IT industries, and are also related to future returns.

Second, we contribute to recent studies that examine the performance and value implications of digital and AI technologies for non-IT firms. Prior studies such as Chen and Srinivasan (2024) and Babina et al (2024) have shown that the adoption of digital and AI technologies drives value in non-IT firms, through improvements in financial performance. Our analysis complements these studies by focusing on a specific dimension of AI investment - AI innovations. Notably, there is a key tension in whether non-IT firms would invest in and benefit from AI innovations. Prior research on digital technologies (Tambe et al, 2020), argue that these technologies (including AI) tend to benefit superstar firms, such as Microsoft and other large tech firms, that are able to accumulate digital capital. On the other hand, local industry knowledge in the application of new GPTs could also provide advantages for non-IT firms to innovate in AI. Our analysis provides empirical support for the latter view, as we find that (1) non-IT firms' AI innovations are highly influential innovations and (2) are associated with improvements in the competition position of firms.

# 2 Conceptual Framework

## 2.1 AI as a General-Purpose-Technology

Bresnahan and Trajtenberg (1995) coined the term General-Purpose-Technologies (GPTs) to describe a special class of technologies that have driven sustained periods of economic growth. These "engines of growth" which include technologies, such as electricity, computers, and the internet, have led to long periods of firm-level and overall economic growth (Lipsey et al, 2005; Petralia 2020). Bresnahan (2010) defines GPTs as exhibiting the following three features: (1) capable of ongoing technical improvements, (2) enabling innovation in application sectors and (3) widely used. These features are important, as they lead to two economic effects that distinguish GPTs relative to other technologies. First, GPTs tend to exhibit a long period of development, giving rise to knowledge accumulation and specialization in the invention of GPTs. Second, GPTs exhibit knowledge spillovers and diffusion in innovation across sectors, which drive operational gains in a broad set of firms.

Recent work studying the economic impact of AI has argued that the complementary group of AI-related technologies - analytics, big data, and machine learning are GPTs (Goldfarb et al, 2023; Cockburn et al, 2019) because of their potential for large scale economic benefits. These potential benefits arise from the fact that the general enabling technology in the GPT sector, spurs widespread innovation across different application sectors. Moreover, AI technologies are also constantly refined through innovation diffusion across general and application sectors. Perhaps due to these reasons, recent work on AI, suggests that there will be large economic benefits from the development and integration of AI technologies with existing business processes (Brynjolfsson et al, 2019).

Based on this discussion, we conjecture that AI innovations will have a substantial impact on the application sectors of AI - the non-IT industries. Thus, we examine the profile of the non-IT firms that engage AI innovations, and also study the valuation implications of AI innovations for these firms. Specifically, (1) we examine the role of knowledge accumulation in the development of AI technologies in non-IT sectors, (2) we examine whether AI innovations create value for non-IT firms and (3) the sources of value for these innovations.

## 2.2 Who develops AI Technologies in Non-IT Industries?

For our first research question, we examine the drivers of AI innovation. A key determinant of AI innovations is prior knowledge of software technologies. One view is that the development of AI technologies could follow the recent economic phenomena of the "superstar" effect. Prior work shows that the superstar effect arises due to complementary technology development that benefits firms that are first to innovate and can accumulate innovations and skills (Autor et al, 2017; Ayyaghari et al, 2023). As GPTs require complementary investments to generate value (Bresnahan and Greenstein, 1996; Bresnahan et al 2002), these technologies are particularly likely to generate a superstar effect. Notably, prior work shows that a few superstar firms have accumulated technical knowledge and organizational capital in digital and software technologies (Tambe et al, 2021). As AI is a subset of digital and software technologies, we expect an accumulation of software knowledge in certain firms that frequently innovate in AI technologies as well. This leads to the prediction that firms with greater prior knowledge of software technologies will tend to invest in more AI technologies. Thus we examine the following hypothesis:

*H1a: Knowledge in software technologies is positively related to future AI innovation.*

Prior knowledge in non-AI technologies could also play a role in determining whether a firm engages in AI innovation. Prior research into GPTs suggests that local complementary knowledge is also important in developing applications of GPTs (Conti et al, 2019; Gambardella et al, 2021). This complementary knowledge could lie in the experience that is developed through the innovation of non-AI technologies. Thus, prior knowledge in non-AI technologies could complement the development of AI innovations as well.

On the other hand, there is also reason to expect that the accumulated knowledge from non-AI innovation could limit new AI innovation. In particular, several papers in the innovation literature argue that firms with a large stock of existing knowledge are less likely to develop technologies in new areas. One reason is that incumbents tend to lack the right incentives to engage in innovation in new technological areas (Christensen, 1997). Another reason is that the rigidness in the innovation architecture limits the incumbent's ability to re-orient the R&D processes to research different technological areas (Henderson and Clark, 1990). Due to the different views of the relationship between prior non-AI knowledge and AI patenting activity in prior work, we pose the following hypothesis in null form:

*H1b: Knowledge in non-AI technologies is not related to future AI innovation.*

## 2.3 Investor Assessment of the Market Value of AI Innovation

Our second research question on the market value of AI innovations, is motivated by prior work in accounting and finance that shows that innovation activities as measured by patenting activity or R&D investments are associated with higher valuations and returns (Lev and Sougiannis, 1989; Sougiannis, 1994; Chan et al, 2001; Hall et al, 2005; Xu and André, 2007; Lin and Wang, 2016; Kogan et al, 2017; Lang and Glaeser, 2023). To contribute to this body of work, we focus on AI innovations, as companies have focused on these innovations in recent years (Giczy et al, 2022). Moreover, recent studies suggest that GPTs, and by extension AI, should be viewed as a distinct priced risk factor (Hsu et al, 2022).

As there is growing consensus that AI is a GPT (Goldfarb et al, 2023; Cockburn et al, 2019), there is much reason to expect large productivity benefits that are associated with AI and associated technologies. Moreover, studies have also argued that AI could enable firms to develop new products and services, such as chatbots, and driverless cars etc. (Brynjolfsson et al, 2019). The potential for new products and greater productivity suggests that AI innovations should be linked with greater sales growth and future cash flows, which consequently should also lead to higher market values for this class of technologies.

Yet, there are also some potential frictions in the development process of these technologies, that might lead investors to ascribe a lower value to these innovations compared to other innovations. GPTs tend to exhibit long-development lags so the benefits of these technologies may take years to fully realize (Bresnahan et al, 2002). One example is the development of computers in the 1970-80s which had no discernible impact on productivity statistics until the 1990s. As a GPT, AI technologies are also likely to face the same uncertainty due to the long lag in development. Brynjolfsson et al (2019) finds that there is limited evidence of AI's impact on aggregate productivity, perhaps due to the long lag between the development of AI and its productivity impact. Thus, there is also reason to expect that investors may not fully value the benefits of AI innovations.

Moreover, the benefits of AI technologies that are developed in the non-IT sector is unclear, as there is limited evidence on whether non-IT companies have the necessary expertise to develop these technologies. A core insight from the literature on GPTs is that there is specialization in the development of GPTs such as AI (Bresnahan and Gambardella, 1998). Thus, the benefits of AI innovation could accrue only to a subset of companies with substantial accumulated knowledge and expertise in AI technologies.

Hence, it is ex ante unclear if the investment in AI innovation is beneficial to non-IT firms on average. Stated formally, we test the following:

*H2: The value of AI innovations is no different from the value of non-AI innovations.*

## 2.4 Drivers of AI Innovations' Value

In the following discussion, we argue that the value of AI innovations stem from two sources, namely, the (1) innovation spillover benefits of AI innovations and (2) the competitive advantages that are conferred from the investment in AI technologies.

### 2.4.1 Innovation Spillover Benefits of AI Innovations

One of the core features of AI technologies, as a GPT, is that it drives continuous innovation across sectors by spurring wide-spread innovation spillovers (Bresnahan et al, 2010). Notably, for AI technologies that are developed in the non-IT sector, these technologies are particularly valuable due to two sources of spillovers. First, AI technologies developed in non-IT firms benefit from technical improvements in the core technologies from the IT sector that spillover into the application or non-IT sectors. Second, AI technologies developed in the non-IT sector are also particularly valuable as these technologies are also likely to spur follow-on innovations in other non-IT applications.

In particular, the notion that non-IT sectors benefit from continual development of the core AI technologies in the IT sector, suggests that AI technologies in the non-IT sector should exhibit gradual increases in value, as the core technical capabilities continue to improve. Notably, the development of AI is characterized by several breakthrough innovations that substantially advanced the capabilities of these technologies. For example, AlexNet, developed by Krizhevsky et al (2012) was a breakthrough that dramatically improved the image recognition capabilities of AI and sparked the deep learning revolution (LeCun et al, 2015). Thus, we expect that these breakthrough events that increased the technical capabilities of AI should play a key role in driving the value of AI innovations:

*H3a: The introduction of breakthrough AI technologies increases the value of AI innovations.*

Moreover, AI technologies developed in the non-IT sector are perhaps also more valued because the quality of these innovations is higher - these technologies are likely to spur future innovations in these sectors. Notably, for the innovator firms, follow-on innovation also provides a private benefit by increasing licensing opportunities for these companies, which would also provide a rationale for why AI innovations are more valued by investors. Perhaps due to this reason, prior research shows that patents that are more highly cited in the future, also tend to exhibit a higher market valuation (Hall et al, 2005; Kogan et al, 2017). Thus, the potential for greater follow-on innovation could be another channel that explains the value of AI innovations, which we investigate further with the following hypothesis:

*H3b: AI innovations spur more future innovations compared to non-AI innovations.*

### 2.4.2 Competitive Advantages of AI Innovations

In addition to the innovation spillover benefits of AI technologies, the existing literature also suggests that AI innovations can confer important competitive advantages for AI-innovators, which should be priced by investors. First, AI technologies are expected to drive substantial productivity benefits in firms (Brynjolfsson et al, 2019). Prior studies suggest that AI and other digital technologies improve production processes (Tambe, 2014; Chen and Srinivasan, 2024), and innovation processes (Cockburn et al, 2019), leading to greater efficiencies within the firm. Thus, there is reason to expect that the investment in AI technologies can enhance firm productivity, which would in turn improve the competitive position of firms.

Second, AI technologies could also be integrated with existing products and services, to create new product offerings (Babina et al, 2024). For example, the recent development of self-driving technologies, robotic cleaners, are new products for consumers that integrate AI technologies with traditional products. These new products and services could be highly valued by consumers, which in turn enables firms to charge a premium for these offerings, and improves their competitive position relative to peers.

Combined, both of these factors suggest that the investment in AI technologies should confer competitive advantages. Thus, we also study the following hypothesis, stated below:

*H4: Firms that invest in AI innovations improve their competitive position relative to peers.*

# 3 Data

Our study primarily leverages the Artificial Intelligence Patent Dataset (AIPD) from the USPTO's Office of the Chief Economist, which encompasses US patents from 1976 to 2023 related to key AI components. These components span a broad spectrum of AI fields, including machine learning, natural language processing, computer vision, speech technology, knowledge processing, AI hardware, evolutionary computation, and planning and control systems. Developed through a sophisticated machine learning methodology, this dataset was meticulously constructed by training and applying a machine learning model that uses patent texts, citations, and claims to accurately identify AI-related innovations (Giczy et al, 2022; Pairolero et al, 2024). The robustness of their classification is further checked through manual, out-of-sample validation by specialized patent examiners, making it an important resource for analyzing AI patent values and its market implications.

Next, we acquire patent market values and links to public firm identifiers using the extended dataset from Kogan et al. (2017). In their study, the authors estimate the private economic value of patents based on stock market reactions to patent grants after controlling for other factors. Specifically, their methodology involves two key steps: first, isolating the impact of patent issuance from unrelated stock market news by focusing on patent announcement returns, and second, separating the stock return related to the patent's value from other unrelated fluctuations. This methodology is executed through a statistical model that accounts for both the anticipated success of the patent and idiosyncratic variations in stock returns, enabling a precise estimation of a patent's contribution to a firm's market value.

Next, we obtain patent characteristics from *PatentsView*, which allows us to observe patent information such as the application and grant date, the identities of assignees and inventors, the technology classes, forward citations, and the texts of patent descriptions. We combine these datasets to construct a final sample with 1,587,948 patents that have information on technology class and can be linked to a public firm assignee, involving 3,184 public non-IT firms with grant years spanning from 2001 to 2023.[5][6]

Finally, in the concluding segment of our analysis, we aggregate our sample to the firm-year level to examine the impact of AI patents on corporate financial performance, which we measure with *Compustat*. After restricting on firm-year observations for non-IT firms with complete financial information for the subsequent year, we compile a comprehensive dataset comprising 79,142 firm-year observations. For details on sample formation, see Table IA1 in the internet appendix.

Additionally, to reduce the impact of outliers, we winsorize continuous variables at the top and bottom 1 percent of the cross-sectional distribution within each year.

# 4 Results

## 4.1 Descriptive Analysis

### 4.1.1 The Evolution of AI Patents

We begin our analysis by examining the transitions and spillovers of AI technologies in public firms from 2001 to 2023. We first present the overall trends in AI innovations across all public firms in Figure 1. At the beginning of our sample period, AI patents granted to public firms were relatively scarce, comprising only about 5200 per year, which represented a modest 9

[5] We chose 2001 as the starting point because the American Inventor Protection Act (AIPA), passed in 2000, mandated the disclosure of filed patent applications, fundamentally altering the patenting process.
[6] We define IT firms as firms within the 737 SIC group (Computer Programming, Data Processing, And Other Computer Related Services Companies). All other firms are defined as Non-IT firms.

percent of the total patents issued. In the following years, we observe a consistent annual growth at an average rate of 14.5 percent, culminating in the issuance of over 90,000 AI patents in the year 2022. Notably, AI patents have become increasingly prominent, representing over 30 percent of the total patents granted to public firms. This trend underscores the rising significance and proliferation of AI technology.

Previous studies argue that AI technologies, as a GPT, should exhibit significant cross-industry spillovers, transitioning from a core set of technologies within the IT sector to application-based technologies in various non-IT sectors (Bresnahan, 2010). As depicted in Figure 2, the development of AI originated in the IT sector and has since permeated into multiple major industries, including retail and wholesale trade, finance, services, and transportation. In Table 1, we further examine the industry distribution of AI patents categorized by 2-digit SIC industries, and we find AI patenting activity in a wide range of 2-digit SIC industries. Unsurprisingly, the Electronic and Other Electrical Equipment and Components sector (SIC code 36) accounts for the largest share of AI patents, with 80,331 patents (~36% of total AI patents). This is followed by the Industrial and Commercial Machinery and Computer Equipment sector (SIC code 35), with 45,656 patents (~21% of total AI patents), and the Transportation Equipment sector (SIC code 37), with 20,130 patents (~9% of total AI patents).

Moreover, in Figure 3, we present additional statistics that focus on the non-IT firms that we examine in our analysis. In this figure, we further explore the increase in AI patenting activity in non-IT industries by analyzing the extensive margin, represented by the share of firms engaged in AI innovation, and the intensive margin, measured by the number of AI patents per firm. We find that the increase in AI patenting activity is primarily driven by the intensive margin, which suggests rising concentration in AI patenting amongst non-IT firms.

### 4.1.2 Summary Statistics of Key Variables

Table 2 presents descriptive statistics for our sample, including both patent-level and firm-year level data. In Panel A, we observe that, on average, 14.6 percent of patents granted to public firms are identified as AI patents. The average patent holds a value of $12.20 million, while the average AI patent holds a value of $17.58 million. At the firm-year level, an average firm is granted 2.14 AI patents and 15.63 patents in each year.

## 4.2 Drivers of AI Innovation

In our first set of analyses, we use the following regression model at the firm level to examine the determinants of initial AI innovation activity in a firm-year panel:

$$AI\ Patent_{it} = \alpha + \beta_1 Log(Software\ Patents_{it}) + \beta_2 Log(NonAI\ Patents_{it})$$
$$+\beta_3 Log(Firm\ Size_{it}) + \beta_4\ R\&D\ Intensity_{it} + \beta_5\ Sales\ Growth_{it} + \beta_6 Leverage_{it}$$
$$+ \beta_7 External\ Finance_{it} + \beta_8 Capital\ Intensity_{it} + \beta_9 Age_{it} + \beta_{10} Sales\ Share_{it}$$
$$+ \beta_{11} HHI_{it} + CPC \times Year\ FE + Industry\ \times Year\ FE + \epsilon_{it}, \quad (1)$$

where the dependent variable, $AI\ Patent$, is an indicator equal to 1 for the firm *i*'s first AI patent year *t* and 0 otherwise (and subsequent observations are dropped). $Log(Software\ Patents)$ is the logarithm of the cumulative stock of software patents held by the firm over a five-year window, weighted by their market value. This variable reflects the firm's accumulated knowledge in software and digital technologies. Additionally, $Log(NonAI\ Patents)$, is the logarithm of the five-year cumulative value of non-AI patents granted to the firm and measures the general domain knowledge of a non-IT firm.

Additionally, we include a range of other firm characteristics that may influence AI innovation. We include proxies for firm size and innovation intensity, with $Log(Firm\ Size)$, the natural logarithm of net sales and $R\&D\ Intensity$, the R&D expenditures to total assets. We also include $Sales\ Growth$, the annual growth in sales, as well as $Leverage$ (the ratio of total debt to total assets) and $External\ Finance$ (the ratio of net external financing to total assets) to control for the firm's financial health and access to funding. Moreover, we also control the firms' fixed assets investment with $Capital\ Intensity$, the ratio of capital expenditures to total assets, and we also include the logarithm of firm age ($Age$). Lastly, we include measures of market competition with $Sales\ Share$, the market share of sales, which represents the firm's competitive position within its industry, and $HHI$, which measures the sales-based industry concentration.

We report the results of the determinant analysis described in Equation (1) in Table 3, using linear probability models with different layers of fixed effects (No FE, Industry and Year FE, Industry x Year FE). Notably, in the first row, we find that the coefficient on value of software patents stock is consistently positive and statistically significant across all specifications. Specifically, the estimated coefficient suggests that a 10 percent increase in the software patenting activity, is associated with a roughly 0.9 percent increase in the probability of the initiation of AI patenting activity. Thus, this results indicates that firms with a higher stock of software patents tend to engage in AI patenting activity, supporting the $H1a$ that posits that prior investments in software innovation create cumulative advantages that encourage non-IT firms to develop AI technologies. Notably, this result aligns with research work examining the "superstar" effect, which suggests that complementary technology development disproportionately benefits firms that are first to innovate and can accumulate innovations (Autor et al., 2017; Ayyagari et al., 2023).

Next, we test the hypothesis regarding the role of knowledge in non-AI technologies in fostering AI innovation ($H1b$). Notably, there is a key tension in this hypothesis. On one hand, complementary technologies could play a crucial role in creating applications of AI, as discussed by Conti et al. (2019) and Gambardella et al. (2021). On the other hand, previous studies also suggest that established firms with large stocks of innovation may exhibit rigidity and lack incentives to enter new domains of innovation (Henderson and Clark, 1998).

In the second row of Table 3, we find that the coefficient on the value of non-AI patents stock is positive and highly significant across all specifications, suggesting that firms with greater stocks of innovation in non-AI technologies are more likely to innovate in AI. In terms of magnitudes, our estimates across all specifications, suggests that a 10 percent increase in the value of non-AI patent stock corresponds to about a 0.4 percent increase in the probability of developing AI technologies. Thus, this finding supports the notion that existing knowledge in non-AI technologies complements AI technology development and facilitates entry into the AI domain. Moreover, we also find that firm age consistently exhibits a positive and significant effect, which further suggests that older firms with established capabilities and institutional knowledge are more likely to innovate in AI.

Additionally, in the specification that adds additional layers of fixed effects (Industry and Year FE, Industry x Year FE), we find that firm size is also consistently positive, consistent with the notion that larger firms have greater resources to invest in AI development (Babina et al, 2024). Lastly, we also find that sales-based market share shows a significantly negative coefficient across these specifications. This suggests that firms with a weaker competitive position are more likely to develop more AI innovations, potentially viewing them as a strategic response to competitive pressures or as a way to address market challenges by improving efficiency or entering new markets.

## 4.3 Are AI Innovations More Valuable?

In the second part of our analysis, we focus on the market value of AI patents, building on prior research that shows that patents generally add value to firms (Kogan et al., 2017; Hall et al., 2005). Thus, to investigate whether AI patents hold greater market value than non-AI patents (*H2*), we estimate the following regression model in a patent-year panel:

$$Patent\ Value_{ijt} = \alpha + \beta_1 AI\ Patents_{ijt} + \beta_2 Log\ Firm\ Size_{jt} + \beta_3 Log\ RetVol_{jt}$$
$$+\beta_4\ \ R\&D\ Intensity_{jt} + \beta_5 R\&D\ Intensity_{jt-1} + \beta_6 R\&D\ Intensity_{jt-2}$$
$$+CPC \times Year\ FE\ +\ Industry \times Year\ FE\ +\ \varepsilon_i\ . \qquad (2)$$

The dependent variable ($Patent\ Value$) is defined as the value of patent $i$'s of firm $j$ granted in year $t$, adjusted to 1982 (million) dollars using the consumer price index (CPI).[7] $AI\ Patent$ is an indicator variable equal to 1 if patent $i$ of firm $j$ in year $t$ is categorized under one or more of the eight AI technology components, identified in the AIPD. The key coefficient of interest in Equation (2) is $\beta_1$ and we expect $\beta_1 > 0$ ( $\beta_1 < 0$) if AI patents are on average more (less) valuable compared to their non-AI counterparts.[8]

Equation (2) also includes both subsection-level cooperative patent classification (CPC) technology classes interacted with grant-year fixed effects ($CPC \times Year\ FE$) and 3-digit SIC industry groups interacted with grant-year fixed effects ($Industry \times Year\ FE$).[9] This approach absorbs time-variant factors specific to technology classes and industry groups, such as unmodeled trends in technological development and industry-level production shocks that may influence the market value of patents. We also include a host of patent-level controls that may systematically affect patents' market value following Kogan et al. (2017). Specifically, we consider logarithm of size ($Log\ Firm\ Size$), the log-transformed return volatility (Log

[7] Notably, this measure of patent value yields a value estimate that is net of the expected capitalized cost of innovation, as the market value of patents is measured with stock returns around the patent grant date. To the extent that markets do not fully capitalize R&D and other innovation-related expenditures into stock prices before the grant date, our research design also includes an array of fixed effects to absorb systematic capitalization-related issues at the technology and industry-level. Moreover, to address differences in capitalization-related issues in high vs low R&D firms, we also control for R&D intensity and its lags.
[8] To the extent that AI patents spur knowledge spillovers and complementary value in innovations outside of the firm that are not captured by market prices, the patent value measured at the firm-level is a lower bound of the value of AI innovations.
[9] The CPC is the latest patent classification scheme that is jointly used by the USPTO and the EPO.

$RetVol$). Additionally, we control for the research input costs, with the R&D intensity ($R\&D\ Intensity$), as well as the lagged values of R&D intensity. Since patent value is a non-negative and highly skewed outcome variable, we also employ Poisson fixed effects models for our regression analyses, as recommended by Cohn et al. (2022). In addition, following Kogan et al. (2017), we cluster the standard errors at the firm-grant year level to account for within-firm correlation over time and to avoid biased estimates.

The analysis of Equation (2) is presented in Table 4. Across all specifications, our main result is that the coefficient on AI patents is positive and significant, indicating that AI patents are more valuable than non-AI patents.[10] Specifically, Columns (1) and (2), which includes CPC-year (industry-year) fixed effects, the analysis shows that AI patents are, on average, 13.7 (19.6) percent more valuable than non-AI patents within each technology class and year (industry and year). Finally, Column (3) includes both CPC-year and industry-year fixed

[10] In the robustness analyses presented in the IA, we re-estimate the model using a linear regression with log(Patent Value) as the dependent variable. As shown in Table IA2, the results remain robust, with a positive and significant coefficient on AI patents. Additionally, we re-run the Poisson model using alternative thresholds for defining AI patents (86 percent and 50 percent), as specified by the AIPD. The results, reported in Table IA3, are consistently positive and significant across all specifications, underscoring the robustness of our findings. Lastly, we also estimate the model with different samples of non-IT firms, based on the NAICS and GICS definition of software firms. These analyses, reported in Table IA4, find quantitatively similar results.

effects, showing that within each industry, CPC group, and year, AI patents are 6.6 percent more valuable than non-AI patents.[11][12][13]

Across all models, we control for firm size, return volatility, and R&D intensity (averaged over the past five years and lagged by one and two years) to address potential confounding factors related to firm characteristics and R&D investments. Notably, we find that the coefficients on R&D intensity and its lags are mostly insignificant, indicating that recent R&D inputs have a limited impact on the market value of patents.

#### 4.3.1 AI Innovations and Return Predictability

Next, we examine whether AI innovation in non-IT firms predicts future returns. Prior research suggests that exploitative innovations are uncertain and its value implications are difficult to process for investors (Fitzgerald et al, 2020), leading to predictable returns. As AI innovations in non-IT firms are applications of new AI technologies, we posit that these innovations are hard for investors to assess, and test whether these innovations yield abnormal returns.

[11] In Figure IA1 of the IA, we demonstrate that the value of AI innovations has been steadily rising over time. Specifically, we analyze the results from Table 4 in three-year intervals, documenting a consistent increase in the value premium of AI patents relative to non-AI patents. Notably, between 2001 and 2006, the market value of AI patents was not significantly different from that of non-AI patents. However, over the subsequent 17 years, the value premium expanded significantly, becoming distinctly positive and statistically significant under different fixed effects specifications. In the most recent three-year period (2020–2023), the value premium peaked at more than 20 percent within CPC-year fixed effects and more than 10 percent within CPC-year and industry-year fixed effects. This overall trend shows that the value premium of AI technologies exhibits a stable and potentially increasing trajectory.

[12] Furthermore, we examine the value premium of AI innovation across technology components. Specifically, we dissect the AI technology into eight distinct components as defined by the AI Patent Database (AIPD), namely, evolutionary computation (EVO), AI hardware (Hardware), knowledge processing (KR), machine learning (ML), natural language processing (NLP), planning and control (Planning), speech (Speech), and computer vision (Vision). In Figure IA2 of the IA, we present two sets of results comparing the value of each AI component to non-AI patents. The first panel includes both CPC-year and SIC-year fixed effects, while the second panel uses only SIC-year fixed effects. Across both specifications, components such as EVO, Hardware, KR, Planning, and Speech consistently exhibit higher value premiums. Notably, Vision is the only component with a market value comparable to non-AI patents, irrespective of the specification.

[13] We do not study firm-level fixed effects in Table 4 as there is limited within-firm variation in AI patenting activity, as the median value of AI patenting in patenting firms is 10 percent. Moreover, AI innovations should also have a complementary impact on other innovations within the firm, which complicates the comparison of AI versus non-AI patenting activity within firms. Nonetheless, in robustness analyses, reported in Table IA5 of the IA, we report the analysis in Table 4 under the firm-year fixed effects specification. While the magnitude of the AI value premium decreases to 0.4 percent, these estimates remain significantly positive, adding further support to our claim that AI innovations are more valuable compared to other types of innovations.

To study the returns of AI innovation, we begin by first forming portfolios based on AI innovation intensity. At the end of June in each year, we first sort firms by above and below median AI patenting activity and overall patenting activity over the prior year. To perform comparisons over AI versus non-AI innovation activity, we assign firms into two portfolios - (1) firms that exhibit above median share of AI patents relative to total patents and above median total patents ("the AI portfolio") and (2) firms that exhibit below median AI median share of AI patents relative to total patents and above median total patents ("the non-AI portfolio"). With these two portfolios, we then track the portfolio return performance over the sample period of July 2001 to December 2023.

To assess the return performance of the portfolios, we implement calendar portfolio tests that include control for risk and mispricing factors. Specifically, we estimate calendar portfolio alphas from the following factor model:

$$RET_t = \alpha + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + \beta_6 MOM_t + \beta_7 MISMGM_t + \beta_8 \; MISPER_t + \epsilon_{it} \,, \quad (3)$$

where the dependent variable is the equal-weighted or capped value-weighted (at the NYSE 80th market capitalization percentile following, Jensen et al, 2023) portfolio return minus the risk-free rate. In Equation (3), we include various controls for risk factors following Fama and French (2015). These factors are namely, $MKT$, the market return minus the risk-free rate, $SMB$, the small minus big portfolio return, $HML$, the high minus low portfolio return, $RMW$, the robust minus weak portfolio return, $CMA$, the conservative minus aggressive portfolio return. In addition, mindful of the potential of mispricing to explain the return performance of AI innovations, we control for mispricing factors by including $MOM$, the momentum factor, and the two mispricing factors from Stambaugh and Yuan (2017) - (1) $MISMGM$, the management mispricing and (2) $MISPER$, the performance mispricing factor.

Table 5 presents our results, which report the portfolio alphas for the equal-weighted specification in Columns (1) to (3) and the capped value-weighted returns from Columns (4) to (6). Across columns, we examine the factor models controlling for the Fama-French 5 factors, these factors plus momentum, and these factors plus the two mispricing factors from Stambaugh and Yuan (2017). In Panel A, we examine the AI portfolio, and we find that this portfolio exhibits positive alpha across all specifications and factor models. Notably, we find that in the model controlling for all risk and mispricing factors, the AI portfolio exhibits a 32 (19) basis point alpha per month for the equal (capped-value) weighted portfolio returns.[14]

In Panel B, we examine the non-AI portfolio, and we do not find significant evidence of abnormal returns in these portfolios. Specifically, we find that the alphas of this portfolio are of lower statistical significance and in economic magnitude, compared to the AI portfolio. Thus, our comparison of these two portfolios suggests that AI innovation yields positive returns, while other types of innovation are not significantly related to future returns.[15]

Additionally, to further analyze the return performance of AI patenting activity, we turn to panel regressions. In these analyses, we regress firm-level returns on an indicator for membership in the AI portfolio, and include additional controls from a baseline regression model in Hirshleifer et al (2013). Specifically, we implement the following regression:

$$RET_{i,t} = \alpha + \beta_1 AI_{i,t} + \sum \gamma_k X_{i,t,k} + Industry \times Year\ FE + \epsilon_{i,t}\ , \tag{4}$$

where $RET$ is firm $i$'s return in excess of the risk-free rate in month $t$, and $AI$ is an indicator for whether the firm is in the AI portfolio. Equation (4) also includes a vector of controls indexed by $k$. To control for overall innovation activity and market risk, we control for the logarithm of

[14] On an unadjusted basis, the equal- (capped-value-) weighted portfolios yield 106 (90) basis point monthly returns in excess of the risk-free rate.

[15] The inferences from our calendar portfolio tests are also robust to an alternative specification of the AI portfolio, formed on firms that exhibit top tercile AI share in patenting and above median patenting activity.

patents filed in the year and the market beta. In addition, we include the group of controls in Hirshleifer et al (2013), namely, log of market equity, log of book-to-market ratio, return-on-assets, asset growth, momentum, R&D intensity, R&D growth indicator (following Eberhart et al., 2004), Advertising intensity, CapEx intensity, net stock issuance and institutional ownership share. Lastly, we include month x 3-digit SIC industry fixed effects in the regression model to control for industry-related factors. All continuous independent variables in this regression model are standardized to zero mean and unit standard deviation.

We report the analysis in Table 6, and we continue to find that the AI portfolio predicts returns. Our estimates, reported in Columns (1) and (2) suggest that after controlling for a host of factors, firms in the AI portfolio yield on average, a 32 basis point monthly return. Furthermore, we find that the loadings on the overall patenting activity variable is statistically insignificant, suggesting that non-AI innovation is not directly linked with future returns.

Moreover, to examine additional robustness, we study an alternative definition of high AI patenting activity, by computing and analyzing the lagged logarithm of AI patenting activity at the monthly-level (and standardized to zero mean and unit standard deviation). This analysis, reported in Columns (3) and (4), suggest that a standard deviation increase in AI patenting activity in the prior month, yields around 7 basis point monthly return.

Overall, our analysis suggests that the portfolio formed on high AI patenting activity in non-IT firms exhibit abnormal return performance. Thus, we find additional support for our claim that these innovations are particularly valued by investors.

## 4.4 Sources of the Value Premium of AI Innovations

Having established that AI patents are more valuable than non-AI patents, this section explores the potential sources of this value premium. As discussed in the conceptual framework, we propose that the incremental value of AI innovations arises from two main channels: the innovation spillover benefits of AI technologies and the competitive advantages conferred by investments in these innovations. We present the results and examine each channel in detail in the following subsections.

#### 4.4.1 Innovation Spillover Benefits of AI Innovations

AI technologies, as GPTs, drive innovation across sectors by spurring widespread spillovers (Bresnahan et al, 2010). These spillovers occur in two ways: the development of core AI technologies can benefit application sectors, and AI technologies developed in application sectors can spur follow-on innovations in other application areas. Motivated by the gradual increase in the value premium of AI innovations over time, which may result from the continual development of core AI technologies, we focus on the breakthrough innovation of AlexNet, developed by Krizhevsky et al. (2012). This innovation dramatically improved the technical capabilities of AI and, as hypothesized in *H3a*, is expected to differentially impact the value of AI innovations in firms better positioned to benefit from these technologies.

To empirically test the spillover impact of the development of core AI technologies on application sectors, through AlexNet, we employ a difference-in-differences design. Specifically, we examine whether firms with high AI potential exhibit differential behavior compared to other firms after the introduction of AlexNet in September 2012. To measure AI potential, we aggregate a task-based measure of AI's suitability in occupational roles (based on a 2020 survey of AI's impact on occupational tasks in Felten et al., 2021) at the firm level, and we sort firms into high (low) AI potential based on their AI suitability scores.

With the AlexNet event and our classification of high and low AI potential firms, we then estimate the following difference-in-differences regression:

$$Patent\ Value_{ijt} = \alpha + \beta_1 Post\ AlexNet_t \times High\ AI\ Potential_j + \beta_2 Log\ Firm\ Size_{jt}$$

$$+\beta_3 Log\ RetVol_{jt} + \beta_4\ \ R\&D\ Intensity_{jt} + \beta_5 R\&D\ Intensity_{jt-1} +$$

$$\beta_6 R\&D\ Intensity_{jt-2}$$

$$+CPC \times Month\ FE\ + Firm\ FE + \ \varepsilon_{it}, \tag{5}$$

where $Post\ AlexNet$ is an indicator variable equal to 1 for periods after the introduction of AlexNet, and $High\ AI\ Potential$ is an indicator for firms with greater AI potential. The coefficient on the interaction term, $Post\ AlexNet \times High\ AI\ Potential$, measures the differential impact of the technological breakthrough on firms with higher AI potential.

The results of this analysis are shown in Table 7. Consistent with *H3a*, we find that the introduction of AlexNet is associated with an increase in the value premium of AI patents in firms that are more exposed to AI technologies, as defined by Felten's exposure index, relative to less exposed firms. Specifically, Column (1), which includes firm and month fixed effects, shows that AI patents granted after AlexNet are 32.3 percent more valuable in firms with greater AI potential compared to other firms. Column (2), which includes firm and CPC-month fixed effects, indicates an even larger effect, as AI patents granted post-AlexNet are 37.5 percent more valuable in firms with greater AI potential compared to other firms. Thus, these findings suggest that breakthroughs, such as AlexNet, which enhance AI's technical capabilities, play a key role in explaining the value of AI innovations, particularly in firms with operations that are better suited for integration with AI technologies.

The causal interpretation of the difference-in-differences model depends on the validity of the parallel trends assumption. To assess this, we estimate a dynamic version of Equation (5) that includes a set of dummy variables for each year before and after AlexNet's introduction, using the 12 months before AlexNet (September 2011 to August 2012) as the benchmark. The results of this dynamic model are presented in Figure 4. Consistent with the parallel trends assumption, we find that the value premium of AI innovations in the pre-period is not statistically different between treated and control firms before 2012. Following AlexNet's introduction, however, the value premium significantly increases in highly AI-exposed firms, confirming the differential impact of this breakthrough event.

Next, we examine whether AI innovations spur more follow-on innovations compared to non-AI innovations (*H3b*) by estimating Equation (2) with forward citations as the dependent variable. The results, presented in Table 8, Panel A, provide strong evidence that AI patents receive significantly more forward citations than non-AI patents across all specifications.[16] Specifically, in our most stringent specification, Column (3), which combines both industry-year and CPC group-year fixed effects, AI patents receive 22.4 percent more forward citations compared to other patents. Thus, these findings support the hypothesis that the higher value premium of AI innovations is partly driven by their superior quality, which enables them to act as a foundation for subsequent innovations.

In Table 8, Panel B, we examine forward citations specifically within the same technology class (CPC group). These results confirm that AI patents receive significantly more citations within their respective CPC groups, with positive and significant coefficients in all columns. In particular, in our most stringent specification, Column (3), which includes industry-year and CPC group-year fixed effects, AI patents receive 27.8 percent more within-CPC group citations compared to non-AI patents. Thus, this finding further underscores the superior quality of AI innovations and their greater ability to spur follow-on innovations within the same technological domain.

To further test whether the higher citations attributed to AI patents is a source of its value premium, we study whether the forward citations in AI patents are related to patent values. We test this question with the sample of AI patents, and implement the model described in Equation

[16] The number of observations varies across specifications due to the separation problem in Poisson regression, where some observations are perfectly predicted and excluded from the estimation process.

(2), but with the inclusion of forward citations as an independent variable. Table 9 reports these results. In Panel A, we analyze the total forward citation of patents, and we find that a 10 percent increase in forward citations under the CPC Group x Year and Industry x Year fixed effect specification, is related to a 0.7 percent increase in AI patent values. In Panel B, we study the total CPC-group forward citations of patents under the same specification, and we also find that a 10 percent increase in CPC-group forward citations is related to a 0.9 percent increase in AI patent values. Thus overall, our analysis across Tables 8 and 9, suggest that AI patents are more highly cited, and the higher-levels of forward citations is a potential source of the AI value premium.

### 4.4.2 Competitive Advantages of AI Innovations

The second hypothesis on the drivers of the value premium of AI innovations (*H4*) suggests that these innovations improve the firm's competitive position by increasing efficiency in operations (Tambe et al, 2014) and facilitates product innovation (Babina et al, 2024).

To empirically test this hypothesis, we examine the association between AI innovations and firm performance. Specifically, we utilize a firm-year panel dataset and estimate the effects of AI patents on accounting performance with the following linear regression model:

$$y_{it+1,2,3} = \alpha + \beta_1 Log(Value\ of\ AI\ Patents\ Stock_{it}) + \beta_2 Log(Value\ of\ Patents\ Stock_{it})$$
$$+\beta_3 R\&D\ Intensity_{it} + \beta_4\ Capital\ Intensity_{it} + \beta_5\ Intangibles\ Intensity_{it}$$
$$+\beta_6 Log(Firm\ Size_{it}) + \beta_7 BooktoMarket_{it} + Firm\ FE + Year\ FE + \epsilon_{it}, \qquad (6)$$

where $y$ represents various accounting performance metrics for firm $i$ in the one to three year ahead ($t+1$, $t+2$, $t+3$), including return-on-sales, gross margins, and sales-based market share which proxy for the firm's competitive positioning and operational efficiency.

The main independent variable in Equation (6) is $Log(Value\ of\ AI\ Patents\ Stock)$, which measures the number of AI patents granted to the firm weighted by their market value in the year. As a control, we also include, $Log(Value\ of\ Patents\ Stock)$, the number of all patents granted to the firm weighted by their market value in the year, which serves as a proxy for the firm's general innovation capacity across all technological domains. Additionally, as controls, we also include the natural logarithm of firm size, measured with net sales and the book-to-market ratio, defined as the ratio of the firm's book value to its market value, to control for the firms' growth potential. We also include controls for investment, such as R&D intensity, defined as the ratio of R&D expenditures to total assets and capital intensity, measured as the ratio of capital expenditures to total assets. Moreover, we also control for intangible intensity, defined as the ratio of intangible assets to total assets, to control for the firm's reliance on intangible resources. Lastly, we also control for firm-level fixed effects (Firm FE) and year fixed effects (Year FE) to address across-firm heterogeneity and time-specific shocks that may influence firm performance. Standard errors are also double-clustered by firm and year level to account for within-firm correlation over time.

Table 10 reports the effects of AI innovation on various measures of firm-level operating performance and the firm's competitive position. Panel A focuses on ROS, showing that the value of AI patents granted in the year, is associated with one and two- year-ahead increases in ROS, even after controlling for firm characteristics and incorporating firm and year fixed effects. Specifically, in the first year after patent grants, we find that a one standard deviation change in AI patenting activity is associated with a 0.3 percent increase in ROS (or 9 percent increase relative to the sample average ROS of 6.5 percent) This finding supports the hypothesis that AI innovations improve production efficiencies and facilitate product innovation, which subsequently enhance firm profitability. Panel B extends this analysis to gross margins, where the value of AI patents have a positive and significant impact across all horizons (one to three years post-patent grant). Notably, a standard deviation change in the value of AI patents is associated with a 0.3 percent increase in gross margins (or 0.7 percent increase compared to the average gross margins of 39.3 percent) These results indicate that firms leveraging AI patents are able to achieve sustained profitability improvements, likely due to superior product offerings with better pricing power or greater production efficiencies derived from innovative capabilities.[17]

Lastly, we test the idea that AI innovations lead to an improvement in the firms' competitive position by studying changes in market share conditional on AI patenting activity. Panel C presents results with sales-based market share as the dependent variable. Consistent with our expectations, the value of AI patents have a positive and significant impact on market share across all horizons. Notably, at the one-year horizon, a one standard deviation change in the value of AI patents is associated with a 0.5 percent increase in market share (or 8 percent relative to the sample average market share of 6.5 percent). These results therefore reinforce the notion that AI innovations not only improve operating performance but also translate into tangible competitive gains for firms.[18]

# 5 Conclusion

GPTs, such as AI, have driven wide-spread and sustained periods of growth throughout economic history. Thus, the recent development of AI technologies has led many to speculate on the large potential value of these technologies as it continues to be applied and integrated

[17] In additional analyses reported in Table IA6 of the IA, we further study the associations between the value of AI patents and future asset turnover, and sales-to-employees. While the associations are broadly statistically insignificant, the associations are positive, and three-year-ahead sales-to-employees exhibits a positive and significant association with the value of AI patents. Thus overall, we find limited evidence of AI's positive impact on fixed asset utilization efficiency, and worker productivity.

[18] In the internet appendix, we further examine the implications of AI patenting activity on competition dynamics at the industry-level. In Table IA7 of the IA, we find that the value of AI patent stock is negatively related to the two- and three-year ahead HHI, suggesting that the gains in market share reported in Table 10, increases industry-level market competition.

into application sectors. Thus, in this study, we analyze the drivers and value implications of AI innovation as it diffuses across application sectors throughout the economy.

Over time, we find that an increasingly concentrated group of non-IT firms are actively involved with developing AI innovations. Notably, we also find that firms that invest in AI innovations for the first time, are also active in software and non-AI innovations, suggesting that prior non-IT industry knowledge in innovation and expertise in software technologies complements the development of AI technologies in non-IT firms.

Consistent with the large and widespread economic benefits that have been predicted by economists, we find that AI patents are more valued than other types of innovations in the same patent classification and industry group. Part of this value premium is likely driven by the increasing technical capabilities of AI technologies, as we show that the introduction of AlexNet increased the value of AI patents in highly exposed AI firms. Moreover, we find further evidence that supports the notion that this value premium is due to the innovation spillover benefits and competitive advantages of AI technologies, as AI patents are associated with higher forward citations, profit margins, gross margins, and market share.

Taken together, our findings provide important practitioner insights on the value of AI technologies. Specifically, our analysis reveals a value premium in AI innovations, due to the knowledge spillovers and market competition advantages of AI. Moreover, we also show that AI innovators in the non-IT firms also exhibit higher returns, as portfolios formed on high AI patenting activity yield significant returns in excess of risk and mispricing factors.

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# Appendix A: Variable definitions

| Variables | Definitions |
|---|---|
| **Patent Analysis Variables** | |
| *AI Patents* | An indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components (including machine learning, natural language processing, computer vision, speech, knowledge processing, AI hardware, evolutionary computation, and planning and control), identified in the Artificial Intelligence Patent Dataset (AIPD). AI patents are identified through a combination of forward citation analysis and a detailed textual analysis of patent descriptions and claims. |
| *First AI Patent* | A binary indicator for whether the firm applies for its first AI patent. |
| *Patent Value* | The patent value, adjusted to 1982 (million) dollars using the CPI, developed by Kogan et al. (2017) |
| *Forward Citations* | The number of forward citations the patent receives. |
| *Log Firm Size* | The natural logarithm of the total sales for the fiscal year. |
| *Log Return Volatility* | The natural logarithm of the standard deviation of a firm's daily stock returns in a year. |
| *R&D Intensity* | R&D expenses scaled by lagged total assets. |
| *Capital Intensity* | Capital expenditures scaled by lagged total assets. |
| *Intangible Asset Intensity* | Intangible assets scaled by lagged total assets. |
| *Sales Growth* | The annual percentage change in firm sales. |
| *Leverage* | The ratio of total debt to total assets. |
| *External Finance* | The ratio of net external financing to total assets. |
| *Age* | The number of years since the firm was established. |
| *High AI Exposure (high_AIOE)* | An indicator variable equal to 1 for patents assigned to firms in the top 10 percent of AI exposure. Firm-level AI exposure is measured by the average AI exposure across all employees in the firm in 2020, where the employee details are drawn from *RevelioLabs*. |
| *Post AlexNet* | An indicator variable equal to 1 for periods after the introduction of AlexNet in September 2012, and 0 otherwise. |
| *ROS* | The ratio of income before extraordinary items to total sales. |
| *Asset Turnover* | The ratio of total sales to the average of lagged and current assets. |
| *Sales-to-Employee* | The ratio of total sales to total employees. |
| *Gross Margin* | The ratio of gross profit to total sales. |
| *Book-to-market* | The ratio of the firm's book value to its market value. |
| *Market Share* | The percentage of total industry sales accounted for by the firm. |
| *Market Concentration (HHI)* | The Herfindahl-Hirschman Index, calculated as the sum of squared market shares of all firms in the industry, representing market concentration. |
| *Log Value of AI Patents* | The natural logarithm of 1 plus the weighted average of granted AI patents in the year, where the weight is determined by the market value of AI patents. |
| *Log Value of Non-AI Patents Stock* | The natural logarithm of 1 plus the weighted average of granted non-AI patents stock over a five-year window, where the weight is determined by the market value of AI patents. |

| | |
|---|---|
| *Log Value of Software Patents Stock* | The natural logarithm of 1 plus the weighted average of granted software patents stock over a five-year window, where the weight is determined by the market value of AI patents. |
| *Log Value of Patents* | The natural logarithm of 1 plus the weighted average of all granted patents in the year, where the weight is determined by the market value of granted patents. |
| **Factor Model Regression Variables:** | |
| *AI Portfolio* | An indicator variable equal to 1 for firms that fall into both the top median of innovation, measured by total patents in the last year leading to June, and the top median of AI patent intensity, defined as the share of AI patents to total patents over the same period. This portfolio is rebalanced annually in July. |
| *MKT* | The excess return on the market, calculated as the value-weighted return of all stocks in CRSP (NYSE, AMEX, and NASDAQ) minus the risk-free rate. |
| *SMB* | The size factor (Small Minus Big), representing the return spread between small-cap and large-cap stocks. |
| *HML* | The value factor (High Minus Low), capturing the return difference between stocks with high book-to-market ratios (value stocks) and those with low book-to-market ratios (growth stocks). |
| *MOM* | The momentum factor, calculated as the return spread between stocks with high past returns (winners) and those with low past returns (losers) over the prior 12 months, excluding the most recent month. |
| *RMW* | The profitability factor (Robust Minus Weak), measuring the return spread between firms with high operating profitability and those with low operating profitability. |
| *CMA* | The investment factor (Conservative Minus Aggressive), which captures the return difference between firms that invest conservatively and those that invest aggressively, based on asset growth. |
| *MIS-MGM* | A mispricing factor that captures the pricing inefficiencies related to firm-level management decisions, such as discretionary accruals and financing activities (Stambaugh and Yuan (2017)). |
| *MIS-PER* | A mispricing factor that accounts for mispricing due to firm performance measures, including past operating profitability (Stambaugh and Yuan (2017)). |
| **Panel Return Regression Variables:** | |
| *Log(1+num AI Patents)* | The natural logarithm of one plus the number of AI patents held by each firm in each month |
| *Log(1+patents)* | The natural logarithm of one plus the number of patents granted to each firm in the past year (July t-1 to June t) or in the past month |
| *Log(1+RD/ME)* | The natural logarithm of one plus annual R&D expenditure divided by year-end market equity. |
| *Log(1+CapEx/ME)* | The natural logarithm of one plus capital expenditures divided by year-end market equity. |
| *Log(1+AD/ME)* | The natural logarithm of one plus advertising expenditure divided by year-end market equity. |
| *RDG* | A dummy variable equal to 1 for firms with significant R&D growth, |

| | |
|---|---|
| | following Eberhart, Maxwell, and Siddique (2004). A firm qualifies if it has R&D intensity of at least 5 percent, increases total R&D spending by at least 5 percent, and raises its R&D-to-assets ratio by at least 5 percent. |
| *Momentum* | The prior 6-month returns (with a one-month gap between the holding period and the current month). |
| *Beta* | Market beta, estimated from a 60-month rolling regression of a firm's monthly excess stock returns on the monthly excess market return. |
| *ME* | Market equity, calculated as stock price times shares outstanding at the end of the fiscal year. |
| *ROA* | Return on assets, defined as income before extraordinary items plus interest expense, divided by lagged total assets. |
| *AG* | Asset growth, measured as the change in total assets divided by lagged total assets. |
| *NS* | Net stock issuance, defined as the change in the natural logarithm of split-adjusted shares outstanding. |
| *IO* | Institutional ownership, measured as the fraction of firm shares outstanding owned by institutional investors. |

**Figure 1. Time Trends of AI Innovation**

This figure presents the trends of AI innovation from 2001 to 2023. The blue line represents the annual number of granted AI patents, while the red line illustrates the percentage of granted AI patents relative to the total number of granted patents filed each year.

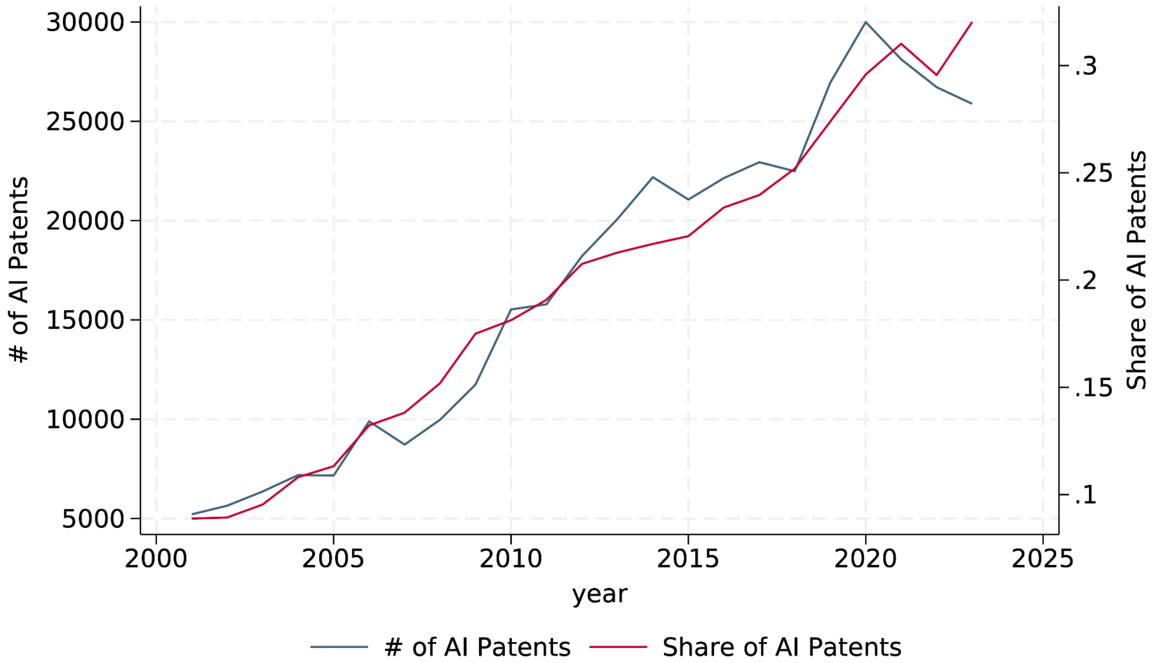

**Figure 2. Cumulative Ratio of AI Patents to All Patents by SIC Divisions across Years**
This figure illustrates the cumulative ratio of granted AI patents to all granted patents by nine SIC divisions across years, from 2001 to 2023. Darker (lighter) colors indicate higher (lower) values. We present 9 industry divisions from SIC codes, namely IT (SIC 737), Retail and Wholesale Trade (SIC 5000-5999), Finance (6000-6799), Non-IT Services (SIC 7000-8999 except SIC 737), Transportation (SIC 4000-4999) , Manufacturing (SIC 2000-3999), Mining (1000-1499), Agriculture (0100-0999), Construction (1500-1799).

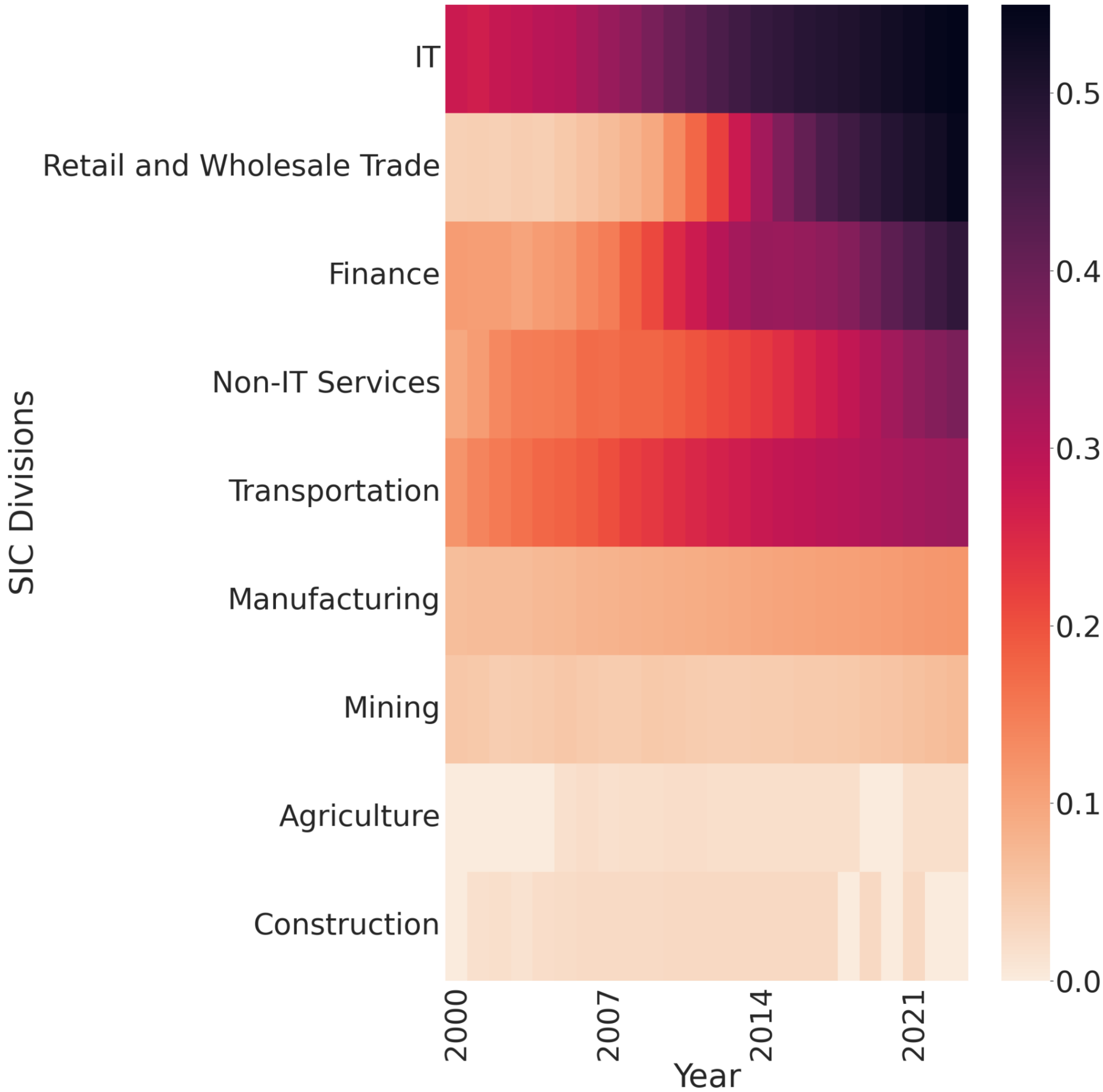

**Figure 3. Intensive Margin and Extensive Margin of AI Innovation by Years**

This figure presents the intensive margin and extensive margin of AI Innovation from 2001 to 2023. The red line plots the average number of granted AI patents per firm (intensive margin) and the blue line plots the proportion of public firms granted at least one AI patent each year (extensive margin).

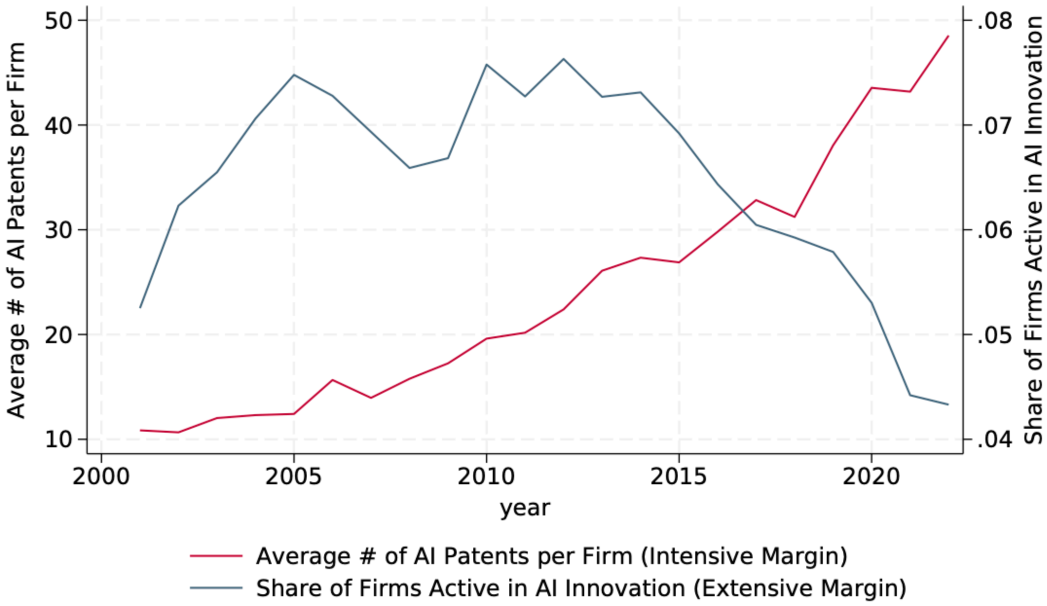

**Figure 4. Parallel Trends: AI Patents Market Value Around the Introduction of AlexNet**
This figure illustrates the estimated $\gamma^k$ values from Equation (4) for the period centered on AlexNet's introduction in September 2012. These values capture the evolving impact of AlexNet on the market value of AI patents over time in highly AI-exposed firms relative to less AI-exposed firms. Each period is distinctly labeled, with the year immediately preceding AlexNet's introduction (September 2011 - August 2012) serving as the benchmark, along with corresponding 95 percent confidence intervals. A vertical red dashed line denotes the initial release of AlexNet for clarity.

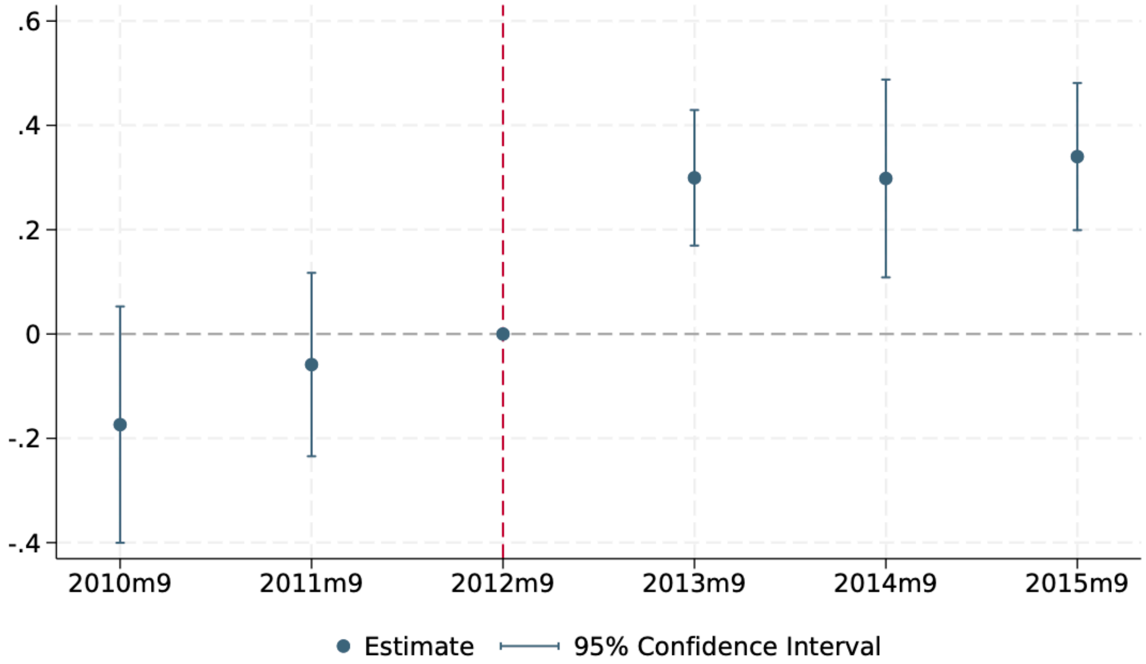

**Table 1. AI Patenting Across Industries**

This table reports the distribution of AI patents across SIC major groups. We report the number of granted AI patents, the number of firms active in AI patenting, and the proportion of public firms active in AI patenting. SIC major groups with fewer than 10 AI parents are excluded. Darker (lighter) colors indicate higher (lower) values.

| SIC Major Group | Description | # of AI Patents | # of Firms Active in AI Patenting | % of Firms Active in AI Patenting |
|---|---|---|---|---|
| 1 | Agricultural Production Crops | 81 | 2 | 5% |
| 10 | Metal Mining | 24 | 7 | 3% |
| 13 | Oil And Gas Extraction | 1690 | 17 | 3% |
| 16 | Heavy Construction Other Than Building Construction Contractors | 28 | 3 | 6% |
| 20 | Food And Kindred Products | 127 | 17 | 6% |
| 21 | Tobacco Products | 69 | 2 | 9% |
| 23 | Apparel And Other Finished Products Made From Fabrics And Similar Materials | 14 | 3 | 3% |
| 24 | Lumber And Wood Products, Except Furniture | 68 | 3 | 5% |
| 25 | Furniture And Fixtures | 283 | 13 | 22% |
| 26 | Paper And Allied Products | 501 | 13 | 10% |
| 27 | Printing, Publishing, And Allied Industries | 168 | 14 | 9% |
| 28 | Chemicals And Allied Products | 2063 | 204 | 11% |
| 29 | Petroleum Refining And Related Industries | 757 | 15 | 18% |
| 30 | Rubber And Miscellaneous Plastics Products | 505 | 10 | 8% |
| 32 | Stone, Clay, Glass, And Concrete Products | 62 | 7 | 9% |
| 33 | Primary Metal Industries | 33 | 8 | 4% |
| 34 | Fabricated Metal Products, Except Machinery And Transportation Equipment | 1063 | 19 | 13% |
| 35 | Industrial And Commercial Machinery And Computer Equipment | 45655 | 226 | 29% |
| 36 | Electronic And Other Electrical Equipment And Components, Except Computer Equipment | 80331 | 322 | 30% |
| 37 | Transportation Equipment | 20130 | 68 | 25% |
| 38 | Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks | 14666 | 234 | 26% |
| 39 | Miscellaneous Manufacturing Industries | 449 | 20 | 15% |
| 40 | Railroad Transportation | 29 | 2 | 8% |
| 41 | Local And Suburban Transit And Interurban Highway Passenger Transportation | 111 | 2 | 11% |

| | | | | |
|---|---|---|---|---|
| 42 | Motor Freight Transportation And Warehousing | 435 | 5 | 6% |
| 45 | Transportation By Air | 192 | 8 | 9% |
| 47 | Transportation Services | 25 | 4 | 6% |
| 48 | Communications | 18184 | 69 | 11% |
| 49 | Electric, Gas, And Sanitary Services | 172 | 28 | 7% |
| 50 | Wholesale Trade-durable Goods | 133 | 17 | 5% |
| 51 | Wholesale Trade-non-durable Goods | 68 | 6 | 3% |
| 52 | Building Materials, Hardware, Garden Supply, And Mobile Home Dealers | 13 | 1 | 4% |
| 53 | General Merchandise Stores | 507 | 3 | 5% |
| 57 | Home Furniture, Furnishings, And Equipment Stores | 13 | 2 | 4% |
| 59 | Miscellaneous Retail | 43 | 2 | 3% |
| 60 | Depository Institutions | 12235 | 17 | 5% |
| 61 | Non-depository Credit Institutions | 7513 | 23 | 1% |
| 62 | Security And Commodity Brokers, Dealers, Exchanges, And Services | 3565 | 11 | 5% |
| 63 | Insurance Carriers | 1169 | 21 | 9% |
| 64 | Insurance Agents, Brokers, And Service | 1637 | 18 | 4% |
| 67 | Holding And Other Investment Offices | 1964 | 21 | 0% |
| 70 | Hotels, Rooming Houses, Camps, And Other Lodging Places | 18 | 1 | 1% |
| 73 | Business Services | 478 | 44 | 2% |
| 78 | Motion Pictures | 331 | 3 | 3% |
| 79 | Amusement And Recreation Services | 272 | 8 | 5% |
| 80 | Health Services | 116 | 12 | 4% |
| 82 | Educational Services | 36 | 6 | 6% |
| 87 | Engineering, Accounting, Research, Management, And Related Services | 3223 | 40 | 13% |

**Table 2. Descriptive Statistics of Sample**

This table presents descriptive statistics for the key variables used in our analyses, including mean, standard deviation, and percentile values. The sample consists of 1,582,277 patent observations for our patent-level analyses that are described in Panel A and 68,224 firm-year level observations for our firm-level analyses that are described in Panel B.

**Panel A. Patent-Level Variables**

| | *N* | *Mean* | *Std. Dev.* | *p25* | *Median* | *p75* |
|---|---|---|---|---|---|---|
| *AI Patents* | 1,582,277 | 0.146 | 0.354 | 0.000 | 0.000 | 0.000 |
| *Patent Value (in millions)* | 1,582,277 | 12.204 | 24.543 | 0.430 | 3.956 | 11700 |
| *AI Patent Value (in millions)* | 231,705 | 17.547 | 30.749 | 1.029 | 5.866 | 18.470 |
| *# of Forward Citations* | 1,582,277 | 8.614 | 21.939 | 0.000 | 2.000 | 7.000 |
| *# of Forward Citations for AI Patents* | 231,705 | 8.576 | 22.524 | 0.000 | 1.000 | 6.000 |
| *Market Value (in billions)* | 1,582,277 | 73.897 | 224.524 | 1.965 | 10.310 | 60.542 |
| *Return Volatility* | 1,582,277 | 4.299 | 5.752 | 1.471 | 2.576 | 4.752 |

**Panel B. Firm-Year Level Variables**

| | *N* | *Mean* | *Std. Dev.* | *p25* | *Median* | *p75* |
|---|---|---|---|---|---|---|
| *ROS* | 79,142 | 0.032 | 0.225 | -0.013 | 0.044 | 0.107 |
| *Asset Turnover* | 79,142 | 0.936 | 0.749 | 0.400 | 0.755 | 1.251 |
| *Sales-to-Employee* | 36,179 | 1.174 | 5.061 | 0.044 | 0.096 | 0.274 |
| *Gross Margin* | 77,914 | 0.393 | 0.232 | 0.227 | 0.365 | 0.546 |
| *Market Share* | 79,142 | 0.065 | 0.154 | 0.001 | 0.007 | 0.044 |
| *HHI* | 79,142 | 0.190 | 0.185 | 0.063 | 0.127 | 0.248 |
| *Book-to-market* | 79,142 | 0.752 | 0.755 | 0.315 | 0.558 | 0.922 |
| *Capital Intensity* | 79,142 | 0.050 | 0.067 | 0.010 | 0.028 | 0.061 |
| *R&D Intensity* | 79,142 | 0.031 | 0.065 | 0.000 | 0.000 | 0.028 |
| *Intangible Asset Intensity* | 79,142 | 0.182 | 0.243 | 0.004 | 0.075 | 0.281 |
| *Firm Size (Sales)* | 79,142 | 4,087.951 | 11,510.064 | 122.236 | 544.589 | 2,335.542 |
| *Sales Growth* | 78,846 | 0.088 | 0.356 | -0.032 | 0.067 | 0.183 |
| *Leverage* | 78,699 | 0.255 | 0.323 | 0.034 | 0.187 | 0.404 |
| *External Finance* | 69,943 | 0.045 | 0.318 | -0.032 | 0.000 | 0.038 |
| *Age* | 77,914 | 18.447 | 15.232 | 7.000 | 14.000 | 26.000 |
| *High AI Exposure (high_AIOE)* | 32,648 | 0.499 | 0.500 | 0.000 | 0.000 | 1.000 |
| *Value of AI Patents Stock* | 79,142 | 28.354 | 333.534 | 0.000 | 0.000 | 0.000 |
| *Value of Non-AI Patents Stock* | 79,142 | 557.320 | 3,693.966 | 0.000 | 0.000 | 4.248 |

| | | | | | | |
|---|---|---|---|---|---|---|
| *Value of Software Patents Stock* | 79,142 | 43.980 | 456.311 | 0.000 | 0.000 | 0.000 |
| *Value of Patents Stock* | 79,142 | 166.387 | 1,133.134 | 0.000 | 0.000 | 0.375 |
| *First AI Patent* | 68,906 | 0.055 | 0.227 | 0.000 | 0.000 | 0.000 |

**Table 3. Determinants of AI Innovation**

This table examines the determinants of AI innovation at the firm level. We investigate the determinants by studying the probability of a firm conducting its first AI innovation. The dependent variable across columns is a binary indicator for whether the firm applies for its first AI patent. The regression models employ linear regression models with multi-way fixed effects. The key independent variables are Value of Software Patents Stock and Value of Non-AI Patents Stock, both measured as the logarithm of the cumulative stock over a five-year window, weighted by their market value. Additional determinant variables include R&D Intensity (R&D expenditures scaled by total assets), Firm Size (log of total sales), Sales Growth (annual percentage change in firm sales), Leverage (total debt-to-assets ratio), External Finance (net external financing-to-assets ratio), Capital Intensity (capital expenditures-to-assets ratio), Age (years since firm establishment), Market Share (firm's percentage of total industry sales), and Market Concentration (HHI). Standard errors are double-clustered by the firm and year, and t-statistics are reported in parentheses. The unit of observation is at the firm-year level, and patenting activity is measured using grant dates within a given year. All variables are winsorized at the top and bottom 1 percent of the cross-sectional distribution. Coefficients marked with *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent, respectively.

| **D.V.: First AI Patent** | (1) | (2) | (3) |
|---|---|---|---|
| *Value of Software Patents Stock* | 0.097*** | 0.091*** | 0.091*** |
| | (7.92) | (7.88) | (7.87) |
| *Value of Non-AI Patents Stock* | 0.040*** | 0.037*** | 0.038*** |
| | (10.21) | (9.46) | (9.45) |
| *R&D Intensity* | 0.146** | 0.038 | 0.016 |
| | (2.52) | (0.62) | (0.24) |
| *Firm Size* | 0.000 | 0.004** | 0.004** |
| | (0.30) | (2.18) | (2.09) |
| *Sales Growth* | -0.001 | 0.000 | 0.000 |
| | (-0.33) | (0.12) | (0.04) |
| *Leverage* | -0.011* | -0.007 | -0.005 |
| | (-1.74) | (-1.29) | (-1.05) |
| *External Finance* | -0.006 | -0.007 | -0.006 |
| | (-0.99) | (-1.20) | (-1.00) |
| *Capital Intensity* | -0.028 | 0.007 | -0.000 |
| | (-0.96) | (0.21) | (-0.01) |
| *Age* | 0.001*** | 0.001*** | 0.001*** |
| | (4.30) | (4.20) | (4.10) |
| *Market Share* | -0.039 | -0.046** | -0.056* |
| | (-1.44) | (-2.14) | (-1.98) |
| *Market Concentration (HHI)* | 0.007 | | |
| | (0.46) | | |
| Industry FE | No | Yes | No |

| | | | |
|---|---|---|---|
| Year FE | No | Yes | No |
| Industry×Year FE | No | No | Yes |
| Observations | 53,911 | 53,911 | 53,911 |
| Adjusted $R^2$ | 0.122 | 0.166 | 0.132 |

**Table 4. Market Value of AI Patents**

This table examines the market value premium of AI patents relative to non-AI patents using fixed-effect Poisson regression models. The dependent variable, Patent Value, is defined as the patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). The main independent variable, AI Patents, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, as defined by the Artificial Intelligence Patent Dataset (AIPD). The table includes additional covariates, including Size, Return Volatility, and R&D Intensity (current, lagged one year, and lagged two years). Industry×Year and CPC×Year fixed effects are included as specified in each column. Standard errors are clustered by the patent grant year-firm, and z-statistics are reported in parentheses. All variables are winsorized at the top and bottom 1 percent of the cross-sectional distribution. Coefficients marked with *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent, respectively.

| **D.V.: Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patent* | 0.196*** | 0.137*** | 0.066* |
| | (2.87) | (2.71) | (1.94) |
| *Firm Size* | 0.214*** | 0.274*** | 0.268*** |
| | (3.34) | (5.79) | (6.04) |
| *Return Volatility* | -0.188* | -0.046 | -0.053 |
| | (-1.83) | (-0.42) | (-0.51) |
| *R&D Intensity (t)* | 1.027 | 1.072 | 0.894 |
| | (1.05) | (1.56) | (1.35) |
| *R&D intensity (t-1)* | -0.952 | 0.112 | 0.056 |
| | (-0.97) | (0.20) | (0.10) |
| *R&D intensity (t-2)* | 0.296 | 1.134 | 1.121 |
| | (0.24) | (1.12) | (1.17) |
| Industry×Year FE | No | Yes | Yes |
| CPC×Year FE | Yes | No | Yes |
| Observations | 1,582,691 | 1,582,696 | 1,582,691 |
| Pseudo $R^2$ | 0.265 | 0.509 | 0.523 |

**Table 5. Returns of Portfolios Sorted by Innovation and AI Patent Intensity**

This table reports the return performance of portfolios formed on innovation and AI patent intensity. The dependent variable is the excess portfolio returns in percentage, measured as the monthly portfolio raw return minus the risk-free rate. Panel A studies portfolios formed based on firms in the top median of innovation, measured by total patents in the last year leading to June, and the top median of AI patent intensity, defined as the share of AI patents to total patents over the same period. Panel B studies portfolios formed based on firms in the top median of innovation but in the bottom median of AI patent intensity. For each panel, the first three columns report equal-weighted (EW) portfolios regressed on the Fama-French 5-factor (FF5), Fama-French 6-factor (FF6), and FF6 with additional mispricing factors (FF6+M). The last three columns report value-weighted (VW) capped portfolios, where firm market capitalizations are winsorized at the NYSE 80th percentile following Jensen et al (2023), regressed on the same factor models. The FF5 model includes market (MKT), size (SMB), value (HML), profitability (RMW), and investment (CMA), following Fama and French (2015). The FF6 model extends FF5 by adding momentum (MOM). The FF6+M model further includes Mispricing-Management (MIS-MGM) and Mispricing-Performance (MIS-PER) factors (Stambaugh and Yuan, 2017). Newey-West standard errors are reported and estimated with a 12-month lag, and t-statistics are reported in parentheses. The sample period covers July 2001 to December 2023. Coefficients marked with *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

**Panel A. Firms in the Top Median of Innovation and AI Patent Intensity**

| D.V.: Return | (1)<br>EW FF5 | (2)<br>EW FF6 | (3)<br>EW FF6+M | (4)<br>VW FF5 | (5)<br>VW FF6 | (6)<br>VW FF6+M |
|---|---|---|---|---|---|---|
| $\alpha$ | 0.455** | 0.492*** | 0.318** | 0.311** | 0.337*** | 0.190** |
| | (2.19) | (2.78) | (2.17) | (2.59) | (3.18) | (2.12) |
| *MKT* | 1.232*** | 1.138*** | 1.175*** | 1.219*** | 1.153*** | 1.189*** |
| | (22.76) | (29.99) | (26.29) | (23.15) | (32.60) | (28.98) |
| *SMB* | 0.473*** | 0.480*** | 0.613*** | 0.079 | 0.084 | 0.189** |
| | (4.63) | (5.24) | (6.75) | (0.79) | (0.96) | (2.43) |
| *HML* | -0.263*** | -0.375*** | -0.295*** | -0.108 | -0.186** | -0.156** |
| | (-2.69) | (-3.96) | (-3.49) | (-1.48) | (-2.48) | (-2.04) |
| *RMW* | -0.799*** | -0.693*** | -0.959*** | -0.623*** | -0.550*** | -0.739*** |
| | (-3.65) | (-4.47) | (-5.83) | (-3.45) | (-4.17) | (-4.98) |
| *CMA* | 0.146 | 0.232 | 0.045 | 0.039 | 0.098 | -0.077 |
| | (0.78) | (1.51) | (0.30) | (0.26) | (0.77) | (-0.74) |
| *MOM* | | -0.270*** | -0.414*** | | -0.187*** | -0.265*** |
| | | (-4.49) | (-5.02) | | (-3.72) | (-4.31) |
| *MIS-MGM* | | | 0.222* | | | 0.262*** |
| | | | (1.77) | | | (2.81) |
| *MIS-PER* | | | 0.462*** | | | 0.291*** |
| | | | (3.41) | | | (3.07) |
| Observations | 269 | 269 | 269 | 269 | 269 | 269 |

**Panel B. Firms in the Top Median of Innovation and Bottom Median of AI Patent Intensity**

| D.V.: Return | (1)<br>EW FF5 | (2)<br>EW FF6 | (3)<br>EW FF6+M | (4)<br>VW FF5 | (5)<br>VW FF6 | (6)<br>VW FF6+M |
|---|---|---|---|---|---|---|
| $\alpha$ | 0.183 | 0.204* | 0.124 | 0.072 | 0.084 | 0.005 |
| | (1.52) | (1.86) | (1.10) | (0.91) | (1.05) | (0.07) |

| | | | | | | |
|---|---|---|---|---|---|---|
| *MKT* | 1.213*** | 1.160*** | 1.169*** | 1.105*** | 1.075*** | 1.082*** |
| | (45.41) | (43.16) | (38.51) | (38.64) | (37.74) | (48.49) |
| *SMB* | 0.538*** | 0.542*** | 0.616*** | 0.243*** | 0.245*** | 0.320*** |
| | (10.13) | (11.09) | (11.43) | (6.45) | (6.90) | (7.85) |
| *HML* | -0.115** | -0.178*** | -0.067 | -0.056 | -0.092** | 0.027 |
| | (-2.22) | (-3.27) | (-1.38) | (-1.38) | (-2.00) | (0.64) |
| *RMW* | -0.359*** | -0.300*** | -0.491*** | -0.116* | -0.082 | -0.280*** |
| | (-3.47) | (-3.95) | (-7.31) | (-1.70) | (-1.46) | (-5.80) |
| *CMA* | 0.180** | 0.228*** | 0.178*** | 0.167** | 0.194*** | 0.148*** |
| | (2.11) | (3.29) | (2.78) | (2.31) | (2.78) | (2.71) |
| *MOM* | | -0.151*** | -0.303*** | | -0.086*** | -0.247*** |
| | | (-3.38) | (-7.11) | | (-2.60) | (-7.45) |
| *MIS-MGM* | | | -0.048 | | | -0.065 |
| | | | (-0.60) | | | (-1.20) |
| *MIS-PER* | | | 0.407*** | | | 0.426*** |
| | | | (7.37) | | | (8.89) |
| Observations | 269 | 269 | 269 | 269 | 269 | 269 |

**Table 6. Panel Regressions of Excess Stock Returns on AI Innovation and Firm Characteristics**

This table reports panel regression analysis of measures of AI innovation activity on monthly excess returns. The dependent variable across columns is the monthly excess return in percentages, measured as the firm's raw return minus the risk-free rate. The key independent variable in Column (1) and (2), AI Portfolio, is an indicator for firms that fall into the top median of total innovation, measured by total patents, and the top median of AI patent intensity, defined as AI patents as a share of total patents. This classification is determined annually based on data from July of year t-1 to June of year t, and the portfolio is rebalanced every July accordingly. Columns (3) and (4) replace the AI Portfolio with Log(1 + num AI patents), which measures the number of AI patents held by each firm in each month. To control for the overall innovation activities that could also drive returns, we control for Log(1 + patents), the number of patents granted to each firm in the past year (July t-1 to June t), for Panel A, or in the previous month, for Panel B. In addition, we control for market beta, and include various controls following Hirshleifer et al (2013), namely, market equity, book-to-market ratio, momentum, ROA, asset growth, R&D intensity, R&D growth, advertising intensity, CapEx intensity, net stock issuance and institutional ownership share. Lastly, we include Month x 3-digit SIC industry fixed effects, to control for industry-level return performance. All variables are winsorized at the 1 percent and 99 percent levels and standardized to zero mean and unit standard deviation. The sample period spans July 2001 to December 2023. Standard errors are double-clustered by 3-digit and month, and t-statistics are reported in parentheses. Coefficients marked with *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

| **D.V.: Return** | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| AI Portfolio | 0.320** | 0.319** | | |
| | (2.50) | (2.49) | | |
| Log(1+AI patents) | | | 0.075*** | 0.057*** |
| | | | (3.00) | (2.65) |
| Log(1+patents) | -0.001 | | -0.037 | |
| | (-0.02) | | (-0.95) | |
| Beta | 0.314** | 0.314** | 0.315** | 0.316** |
| | (2.27) | (2.27) | (2.28) | (2.29) |
| Log(1+RD/ME) | 0.149*** | 0.149*** | 0.147*** | 0.149*** |
| | (2.84) | (2.85) | (2.80) | (2.82) |
| RDG | 0.021 | 0.021 | 0.021 | 0.020 |
| | (1.23) | (1.24) | (1.22) | (1.21) |
| Log(ME) | 0.068 | 0.067 | 0.078 | 0.068 |
| | (0.69) | (0.71) | (0.82) | (0.71) |
| Log(BTM) | 0.077 | 0.077 | 0.078 | 0.077 |
| | (1.07) | (1.07) | (1.08) | (1.07) |
| Momentum | -0.235* | -0.235* | -0.234* | -0.234* |
| | (-1.89) | (-1.89) | (-1.90) | (-1.89) |
| Log(1+AD/ME) | 0.266*** | 0.266*** | 0.265*** | 0.264*** |
| | (3.47) | (3.48) | (3.46) | (3.45) |
| Log(1+CapEx/ME) | 0.033 | 0.033 | 0.031 | 0.028 |
| | (0.36) | (0.36) | (0.34) | (0.31) |
| ROA | 0.514 | 0.514 | 0.491 | 0.498 |
| | (0.82) | (0.82) | (0.78) | (0.79) |
| AG | -0.137*** | -0.137*** | -0.137*** | -0.136*** |
| | (-2.95) | (-2.95) | (-2.96) | (-2.94) |

| | | | | |
|---|---|---|---|---|
| NS | -0.117*** | -0.117*** | -0.116*** | -0.116*** |
| | (-2.67) | (-2.68) | (-2.66) | (-2.66) |
| IO | -0.018 | -0.018 | -0.027 | -0.034 |
| | (-0.46) | (-0.47) | (-0.71) | (-0.93) |
| Month×SIC3 FE | Yes | Yes | Yes | Yes |
| Observations | 166,738 | 166,738 | 166,738 | 166,738 |
| Adjusted $R^2$ | 0.251 | 0.251 | 0.251 | 0.251 |

**Table 7. AlexNet and the Value Premium of AI Innovations**

This table examines the impact of the introduction of AlexNet on the market value premiums of AI patents for highly AI-exposed firms relative to less AI-exposed firms. The analysis uses a fixed effect Poisson regression with a sample spanning two years before and after AlexNet's introduction in September 2012. The main independent variable of interest, High AIOE, is an indicator variable equal to 1 for firms in the top 10 percent of AI exposure and 0 otherwise. Post AlexNet is a binary variable equal to 1 for periods after AlexNet's introduction and 0 otherwise. Fixed effects vary across specifications as noted. Standard errors are clustered by firm-year, and z-statistics are reported in parentheses. Coefficients marked with *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent, respectively.

| **D.V.: AI Patent Value** | (1) | (2) |
|---|---|---|
| *Post AlexNet×HighAIOE* | 0.323*** | 0.375*** |
| | (4.34) | (4.70) |
| *Firm Size* | 0.149 | 0.169 |
| | (1.34) | (1.52) |
| *Return Volatility* | 0.142*** | 0.137*** |
| | (3.46) | (3.11) |
| *R&D Intensity (t)* | -3.567*** | -3.455*** |
| | (-2.65) | (-2.67) |
| *R&D intensity (t-1)* | -1.644*** | -1.567*** |
| | (-2.88) | (-2.79) |
| *R&D intensity (t-2)* | 0.034 | -0.002 |
| | (0.05) | (-0.00) |
| Firm FE | Yes | Yes |
| Month FE | Yes | No |
| CPC×Month FE | No | Yes |
| Observations | 43,329 | 43,329 |
| Pseudo $R^2$ | 0.763 | 0.774 |

**Table 8. AI Patents and Forward Citations**

This table examines the forward citations of AI patents relative to non-AI patents using fixed-effect Poisson regressions. In Panel A, the dependent variable is the total number of forward citations a patent receives, while in Panel B, it is the number of forward citations a patent receives from patents within the same CPC group. The main independent variable, AI Patents, is an indicator equal to 1 for patents categorized as AI patents. Fixed effects vary across specifications as noted. Standard errors are clustered by firm-year, and z-statistics are reported in parentheses. Coefficients marked with *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent, respectively.

**Panel A. Forward Citations**

| **D.V.: Forward Citations** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patents* | 0.348*** | 0.256*** | 0.224*** |
| | (8.86) | (7.39) | (8.81) |
| *Firm Size* | -0.055*** | -0.079*** | -0.055*** |
| | (-2.92) | (-5.75) | (-3.31) |
| *Return Volatility* | -0.016 | -0.039 | -0.023 |
| | (-0.33) | (-1.03) | (-0.54) |
| *R&D Intensity (t)* | 0.114 | 0.086 | 0.098 |
| | (0.51) | (0.35) | (0.52) |
| *R&D intensity (t-1)* | -0.007 | -0.126 | -0.032 |
| | (-0.03) | (-0.50) | (-0.16) |
| *R&D intensity (t-2)* | 0.215 | 0.129 | 0.167 |
| | (0.84) | (0.46) | (0.73) |
| Industry×Year FE | Yes | No | Yes |
| CPC×Year FE | No | Yes | Yes |
| Observations | 1,580,991 | 1,581,337 | 1,579,581 |
| Pseudo $R^2$ | 0.344 | 0.340 | 0.370 |

**Panel B. CPC-Group Citations**

| **D.V.: CPC-Group Citations** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patent* | 0.116*** | 0.140*** | 0.278*** |
| | (3.84) | (3.42) | (5.00) |
| *Firm Size* | -0.039** | -0.058*** | -0.032 |
| | (-2.00) | (-3.09) | (-1.42) |
| *Return Volatility* | -0.016 | -0.004 | -0.000 |
| | (-0.31) | (-0.08) | (-0.01) |
| *R&D Intensity (t)* | 0.165 | 0.218 | 0.279 |
| | (0.72) | (0.71) | (1.00) |
| *R&D Intensity (t-1)* | 0.217 | 0.135 | 0.314 |
| | (0.78) | (0.39) | (0.91) |
| *R&D Intensity (t-2)* | 0.455 | 0.454 | 0.596* |
| | (1.53) | (1.29) | (1.77) |
| Industry×Year FE | Yes | No | Yes |
| CPC×Year FE | Yes | Yes | No |
| Observations | 1,582,691 | 1,576,489 | 1,578,484 |

| | | | |
|---|---|---|---|
| Pseudo $R^2$ | 0.309 | 0.276 | 0.263 |

**Table 9. Value of AI Patents and Forward Citations**

This table examines the relationship between AI patent value and forward citations using fixed-effect Poisson regression models. The sample includes all AI patents, and the dependent variable in all regressions is AI patent value, measured as the patent value adjusted to 1982 million dollars using the Consumer Price Index (CPI), following Kogan et al. (2017). The key independent variables are Log Citations (Panel A) and Log CPC-Group Citations (Panel B), capturing the total number of forward citations a patent receives and the number of citations received from patents within the same CPC group, respectively. Fixed effects vary across specifications as noted. Standard errors are clustered at the firm-year level, and z-statistics are reported in parentheses. Coefficients marked with *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

**Panel A. Forward Citations**

| **D.V.: AI Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *Log Citations* | 0.075*** | 0.191*** | 0.076*** |
| | (3.51) | (6.43) | (3.55) |
| *Firm Size* | 0.314*** | 0.266*** | 0.307*** |
| | (4.66) | (3.47) | (4.66) |
| *Return Volatility* | 0.021 | -0.037 | 0.020 |
| | (0.12) | (-0.28) | (0.12) |
| *R&D Intensity (t)* | -1.542 | -2.476** | -1.552 |
| | (-0.97) | (-2.34) | (-0.95) |
| *R&D intensity (t-1)* | -0.223 | -2.295*** | -0.164 |
| | (-0.34) | (-6.67) | (-0.25) |
| *R&D intensity (t-2)* | 3.065 | 1.472 | 2.903 |
| | (1.41) | (0.73) | (1.37) |
| Industry×Year FE | Yes | No | Yes |
| CPC×Year FE | No | Yes | Yes |
| Observations | 231,779 | 231,778 | 231,778 |
| Pseudo $R^2$ | 0.572 | 0.272 | 0.579 |

**Panel B. CPC-Group Citations**

| **D.V.: AI Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *Log CPC-Group Citations* | 0.095*** | 0.225*** | 0.094*** |
| | (3.57) | (6.59) | (3.46) |
| *Firm Size* | 0.313*** | 0.269*** | 0.307*** |
| | (4.62) | (3.40) | (4.65) |
| *Return Volatility* | 0.020 | -0.041 | 0.020 |
| | (0.12) | (-0.30) | (0.11) |
| *R&D Intensity (t)* | -1.558 | -2.528** | -1.563 |
| | (-0.98) | (-2.42) | (-0.97) |
| *R&D Intensity (t-1)* | -0.222 | -2.268*** | -0.157 |
| | (-0.34) | (-6.62) | (-0.24) |

| | | | |
|---|---|---|---|
| *R&D Intensity (t-2)* | 3.050 | 1.496 | 2.893 |
| | (1.40) | (0.74) | (1.36) |
| Industry×Year FE | Yes | No | Yes |
| CPC×Year FE | No | Yes | Yes |
| Observations | 231,779 | 231,778 | 231,778 |
| Pseudo R² | 0.572 | 0.273 | 0.579 |

**Table 10. AI Innovation and Competitive Advantages**

This table examines the effects of AI innovation on return-on-sales (ROS), gross margins and sales-based market share over the three years following patent grants. The accounting metrics are evaluated one year after the patent grant (Column 1), two years post-grant (Column 2), and three years post-grant (Column 3). The sample includes firms that have at least three years of forward data for the dependent variable. Panel A, reports the analysis with ROS as the dependent variable. Panel B, reports the analysis with gross margins as the dependent variable. Panel C, reports the analysis with gross margins as the dependent variable. The independent variables include the market value-weighted sum of AI patents and all granted patents, calculated using the market value as weights and log-transformed (log + 1). Control variables include R&D Intensity, Capital Intensity, Intangible Assets Intensity, Firm Size, and Book-to-Market Ratio. Firm and Year fixed effects are included in all models. All variables are winsorized at the 1 percent and 99 percent levels and standardized to zero mean and unit standard deviation. Standard errors are double-clustered by firm and fiscal year, and t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10 percent, 5 percent, and 1 percent, respectively.

**Panel A. ROS**

| **D.V.: ROS** | (1) Forward 1 year | (2) Forward 2 years | (3) Forward 3 years |
|---|---|---|---|
| *Value of AI Patents* | 0.003** | 0.003** | 0.002 |
| | (2.11) | (2.23) | (1.62) |
| *Value of Patents* | 0.002 | 0.000 | -0.001 |
| | (0.94) | (0.11) | (-0.41) |
| *R&D Intensity* | -0.006* | -0.003 | -0.002 |
| | (-1.85) | (-0.81) | (-0.54) |
| *Capital Intensity* | 0.005** | -0.001 | -0.001 |
| | (2.48) | (-0.61) | (-0.21) |
| *Intangible Assets Intensity* | -0.010*** | -0.008*** | -0.008*** |
| | (-4.56) | (-3.80) | (-4.07) |
| *Firm Size* | -0.019*** | -0.046*** | -0.056*** |
| | (-2.93) | (-6.10) | (-6.66) |
| *Book-to-Market Ratio* | -0.040*** | -0.020*** | -0.010*** |
| | (-6.24) | (-4.35) | (-2.93) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 51,072 | 51,072 | 51,072 |
| Adjusted R² | 0.511 | 0.503 | 0.500 |

**Panel B. Gross Margins**

| **D.V.: Gross Margins** | (1) Forward 1 year | (2) Forward 2 years | (3) Forward 3 years |
|---|---|---|---|

| | | | |
|---|---|---|---|
| *Value of AI Patents* | 0.003** | 0.003** | 0.003** |
| | (2.41) | (2.54) | (2.27) |
| *Value of Patents* | 0.001 | -0.000 | -0.001 |
| | (0.64) | (-0.06) | (-0.68) |
| *R&D Intensity* | 0.007** | 0.004 | 0.003** |
| | (2.76) | (1.66) | (2.23) |
| *Capital Intensity* | 0.004** | 0.002 | 0.003 |
| | (2.79) | (1.26) | (1.53) |
| *Intangible Assets Intensity* | 0.005*** | 0.004*** | 0.003* |
| | (3.27) | (3.27) | (2.06) |
| *Firm Size* | -0.028*** | -0.038*** | -0.040*** |
| | (-5.10) | (-5.48) | (-6.25) |
| *Book-to-Market Ratio* | -0.018*** | -0.010*** | -0.005** |
| | (-5.91) | (-4.14) | (-2.44) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 50,286 | 50,286 | 50,286 |
| Adjusted $R^2$ | 0.851 | 0.853 | 0.854 |

**Panel C: Sales-Based Market Share**

| **D.V.: Market Share** | (1)<br>Forward 1 year | (2)<br>Forward 2 years | (3)<br>Forward 3 years |
|---|---|---|---|
| *Value of AI Patents* | 0.005** | 0.004** | 0.004** |
| | (2.72) | (2.12) | (2.40) |
| *Value of Patents* | 0.004 | 0.004 | 0.003 |
| | (1.41) | (1.65) | (1.30) |
| *R&D Intensity* | -0.002*** | -0.002*** | -0.001** |
| | (-3.17) | (-3.14) | (-2.39) |
| *Capital Intensity* | -0.001 | -0.001 | -0.001 |
| | (-0.71) | (-0.89) | (-0.91) |
| *Intangible Assets Intensity* | 0.002 | 0.001 | 0.002 |
| | (1.43) | (1.10) | (1.45) |
| *Firm Size* | 0.036*** | 0.030*** | 0.025*** |
| | (6.14) | (5.70) | (5.80) |
| *Book-to-Market Ratio* | 0.000 | -0.000 | -0.001 |
| | (0.01) | (-0.46) | (-0.86) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 51,072 | 51,072 | 51,072 |
| Adjusted $R^2$ | 0.855 | 0.858 | 0.859 |

# Internet Appendix for
# The Value of AI Innovations in Non-IT Firms

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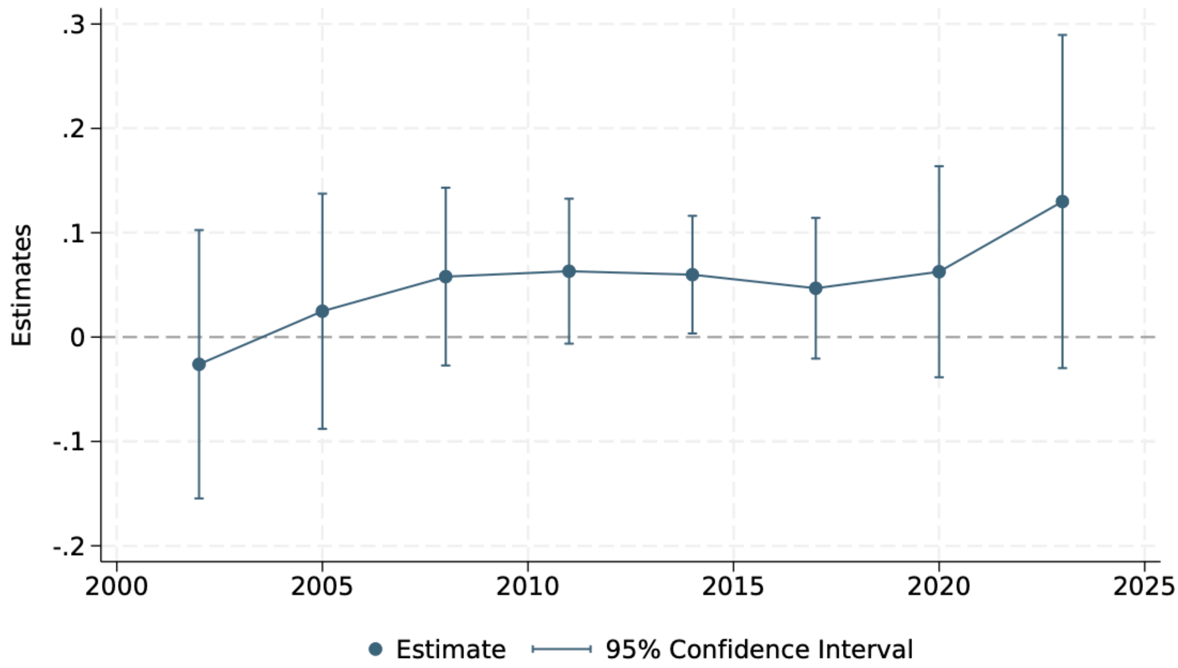
**Figure IA1. AI Patents Value Premium by Time Periods**

This figure includes two panels presenting the estimated $\beta_1$ values from Equation (1), which capture the market value premium of AI patents compared to non-AI patents across eight distinct three-year periods from 2001 to 2023. Accompanying each estimate are the corresponding 95% confidence intervals.

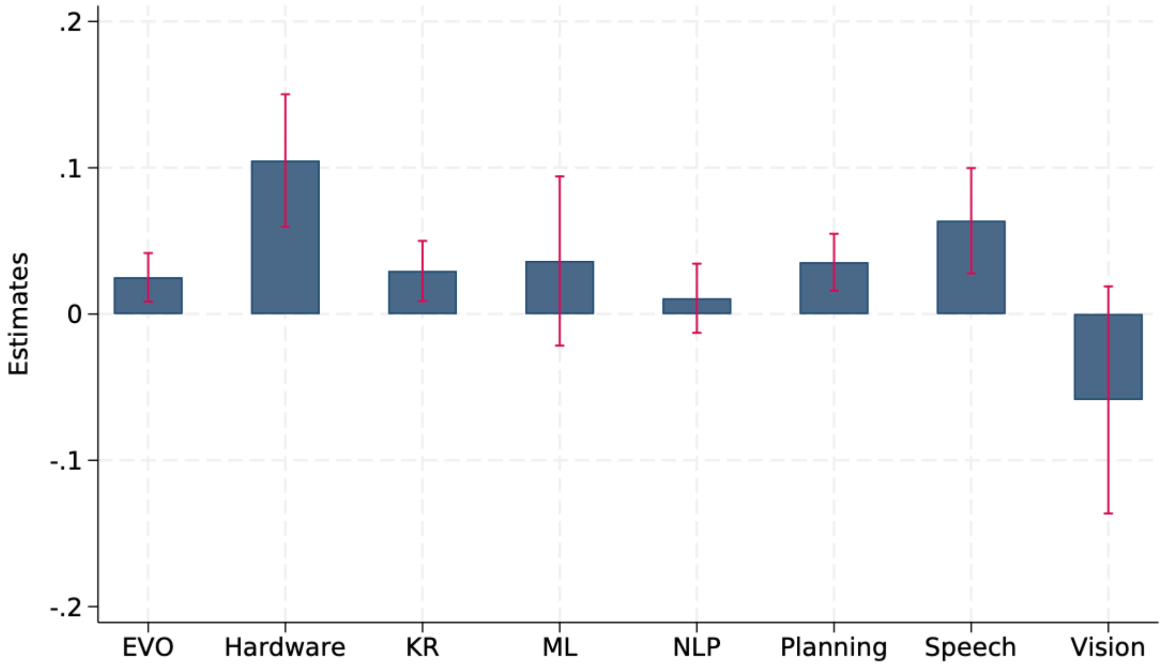

Panel A: Estimated values with CPC patent classification-year fixed effects.



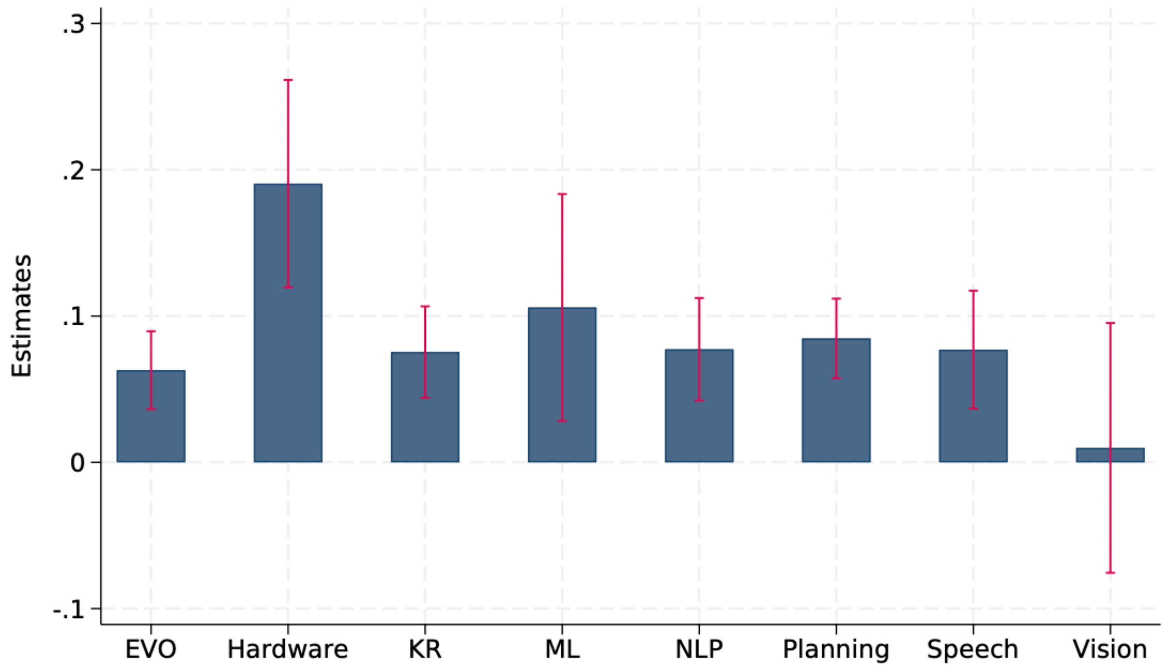

Panel B: Estimate values with CPC patent classification-year and SIC-year fixed effects.

**Figure IA2. AI Patents Value Premium by AI Technology Components**

This figure includes two panels presenting the estimated $\beta_1$ values from Equation (2), which measure the market value premium of AI patents compared to non-AI patents across eight distinct AI technology components: evolutionary computation (EVO), AI hardware (Hardware), knowledge processing (KR), machine learning (ML), natural language processing (NLP), planning and control (Planning), speech (Speech), and computer vision (Vision). The first panel shows estimates with CPC group-year fixed effects, while the second panel includes both CPC group-year and industry-year fixed effects. Accompanying each estimate are the corresponding 95% confidence intervals, indicated by red lines.




Panel A: Estimated values with CPC patent classification-year fixed effects.




Panel B: Estimated values with CPC patent classification-year and industry-year fixed effects.

**Table IA1. Sample Composition**

This table summarizes the composition of the sample, including the distribution of patents, firm-years, and firms. Panel A reports the total number of patents for the full sample and non-IT firms, divided into AI patents and non-AI patents. Panel B provides counts of firm-years and firms for the full sample, the non-IT sample, and subsets of non-IT firms engaging in general and AI-specific innovations.

**Panel A: Patent Counts**

| Category | Number of Patents |
|---|---|
| **Full Sample** | |
| All | 1,878,756 |
| AI Patents | 390,027 |
| Non-AI Patents | 1,488,729 |
| **Non-IT Firms** | |
| All | 1,587,948 |
| AI Patents | 232,616 |
| Non-AI Patents | 1,355,332 |

**Panel B: Firm and Firm-Year Counts**

| Category | Number of Firm-Years | Number of Firms |
|---|---|---|
| Full Sample | 81,649 | 9,538 |
| Non-IT Sample | 79,142 | 9,368 |
| Non-IT Firms with Innovations | 20,815 | 3,184 |
| Non-IT Firms with AI Innovations | 8,083 | 1,470 |

**Table IA2. Robustness Analysis: Market Value of AI Patents Using Linear Regression**

This table examines the market value premium of AI patents relative to non-AI patents using a fixed-effect linear regression model. The dependent variable, Log Patent Value, is the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). The main independent variable, AI Patents, is an indicator equal to 1 if a patent is categorized as AI under the Artificial Intelligence Patent Dataset (AIPD). Control variables include Size, Return Volatility, and R&D Intensity (current, lagged one year, and lagged two years). IndustryYear, CPCYear, and FirmYear fixed effects are included as specified. Standard errors are clustered by patent grant year-firm, and t-statistics are reported in parentheses. All variables are winsorized at the top and bottom 1 percent of the cross-sectional distribution and defined in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent, respectively.

| **D.V.: Log Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patents* | 0.476*** | 0.365*** | 0.226*** |
| | (3.10) | (4.23) | (3.49) |
| *Size* | -0.062 | 0.094 | 0.100 |
| | (-0.59) | (0.85) | (0.98) |
| *Return Volatility* | -0.534* | -0.272 | -0.276 |
| | (-1.89) | (-0.87) | (-0.99) |
| *R&D Intensity (t)* | 1.808 | 2.298*** | 2.058** |
| | (1.22) | (3.03) | (2.58) |
| *R&D Intensity (t-1)* | 0.766 | 1.419* | 1.363* |
| | (0.46) | (1.92) | (1.74) |
| *R&D Intensity (t-2)* | 1.504 | 4.304 | 4.168* |
| | (0.84) | (1.68) | (1.78) |
| Industry×Year FE | No | Yes | Yes |
| CPC×Year FE | Yes | No | Yes |
| Observations | 1,582,691 | 1,582,696 | 1,582,691 |
| Adjusted $R^2$ | 0.174 | 0.416 | 0.453 |

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**Table IA3. Robustness Analysis: Market Value of AI Patents Using Different Thresholds for AI Patents**

This table examines the market value premium of AI patents relative to non-AI patents using a fixed effect Poisson regression model under different thresholds for defining AI patents. The dependent variable, Patent Value, is the patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). The main independent variable, AI Patents, is an indicator variable equal to 1 if a patent is categorized as AI under the Artificial Intelligence Patent Dataset (AIPD). Panel A uses an 86 percent threshold, while Panel B uses a 50 percent threshold. Control variables include Size, Return Volatility, and R&D Intensity (current, lagged one year, and lagged two years). Industry x Year, CPC x Year, and Firm x Year fixed effects are included as noted. Standard errors are clustered by patent grant year-firm, and z-statistics are reported in parentheses. All variables are winsorized at the top and bottom 1 percent of the cross-sectional distribution and defined in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent, respectively.

**Panel A. 86 Percent Threshold**

| **D.V.: Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patents* | 0.197*** | 0.140*** | 0.070** |
| | (2.89) | (2.79) | (2.05) |
| *Size* | 0.214*** | 0.274*** | 0.268*** |
| | (3.34) | (5.80) | (6.04) |
| *Return Volatility* | -0.188* | -0.046 | -0.053 |
| | (-1.83) | (-0.42) | (-0.51) |
| *R&D Intensity (t)* | 1.027 | 1.071 | 0.894 |
| | (1.05) | (1.56) | (1.35) |
| *R&D Intensity (t-1)* | -0.952 | 0.112 | 0.056 |
| | (-0.97) | (0.20) | (0.10) |
| *R&D Intensity (t-2)* | 0.296 | 1.133 | 1.121 |
| | (0.24) | (1.12) | (1.17) |
| Industry×Year FE | No | Yes | Yes |
| CPC×Year FE | Yes | No | Yes |
| Observations | 1,582,691 | 1,582,696 | 1,582,691 |
| Pseudo $R^2$ | 0.265 | 0.509 | 0.523 |

**Panel B. 50 Percent Threshold**

| **D.V.: Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patents* | 0.183*** | 0.145*** | 0.080** |
| | (2.87) | (3.13) | (2.46) |
| *Size* | 0.214*** | 0.273*** | 0.268*** |
| | (3.33) | (5.80) | (6.04) |
| *Return Volatility* | -0.188* | -0.046 | -0.053 |
| | (-1.83) | (-0.42) | (-0.51) |
| *R&D Intensity (t)* | 1.024 | 1.063 | 0.890 |
| | (1.05) | (1.55) | (1.34) |
| *R&D Intensity (t-1)* | -0.957 | 0.108 | 0.055 |
| | (-0.98) | (0.20) | (0.10) |
| *R&D Intensity (t-2)* | 0.296 | 1.130 | 1.123 |
| | (0.24) | (1.12) | (1.17) |
| Industry×Year FE | No | Yes | Yes |
| CPC×Year FE | Yes | No | Yes |
| Observations | 1,582,691 | 1,582,696 | 1,582,691 |
| Pseudo $R^2$ | 0.265 | 0.510 | 0.523 |

**Table IA4. Market Value of AI Patents (Alternative IT Sector Definitions)**

This table examines the market value premium of AI patents relative to non-AI patents using fixed-effect Poisson regression models, employing an alternative definition of the IT sector. The dependent variable, Patent Value, is measured as the patent value, adjusted to 1982 million dollars using the Consumer Price Index (CPI), as developed by Kogan et al. (2017). The key independent variable, AI Patents, is an indicator equal to 1 if a patent is categorized under one or more of the eight AI technology components, as defined by the Artificial Intelligence Patent Dataset (AIPD). Panel A defines the IT sector using NAICS industry codes, specifically 5112, 5191, 5182, 5415, 5141, and 5181. Panel B defines the IT sector based on GICS industry group 4510 (Software & Services). The model includes additional covariates such as Size, Return Volatility, and R&D Intensity (current, lagged one year, and lagged two years). The model includes additional covariates including Size, Return Volatility, and R&D Intensity (current, lagged one year, and lagged two years). Fixed effects for Industry×Year, CPC×Year, and Firm×Year are included as specified in each column. Standard errors are clustered by patent grant year-firm, and z-statistics are reported in parentheses. All variables are winsorized at the 1 percent and 99 percent levels of the cross-sectional distribution and are defined as outlined in Appendix A. Coefficients marked with *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

**Panel A. Non-IT Firms Based on NAICS Definition**

| **D.V.: Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patent* | 0.194*** | 0.126*** | 0.059* |
| | (2.96) | (2.68) | (1.86) |
| *Firm Size* | 0.232*** | 0.310*** | 0.304*** |
| | (3.51) | (5.26) | (5.34) |
| *Return Volatility* | -0.142 | 0.035 | 0.028 |
| | (-1.29) | (0.28) | (0.23) |
| *R&D Intensity (t)* | 0.738 | 0.826 | 0.690 |
| | (0.77) | (1.09) | (0.96) |
| *R&D intensity (t-1)* | -1.217 | -0.054 | -0.096 |
| | (-1.44) | (-0.11) | (-0.20) |
| *R&D intensity (t-2)* | 0.944 | 1.683 | 1.604 |
| | (0.80) | (1.59) | (1.59) |
| Industry×Year FE | No | Yes | Yes |
| CPC×Year FE | Yes | No | Yes |
| Observations | 1,601,384 | 1,601,389 | 1,601,384 |
| Pseudo $R^2$ | 0.268 | 0.509 | 0.522 |

**Panel B. Non-IT Firms Based on GICS Definition**

| **D.V.: Patent Value** | (1) | (2) | (3) |
|---|---|---|---|
| *AI Patent* | 0.223*** | 0.127*** | 0.054* |
| | (3.30) | (2.71) | (1.73) |
| *Firm Size* | 0.226*** | 0.294*** | 0.291*** |
| | (3.70) | (6.46) | (6.68) |

| | | | |
|---|---|---|---|
| *Return Volatility* | -0.132 | -0.003 | -0.009 |
| | (-1.27) | (-0.03) | (-0.08) |
| *R&D Intensity (t)* | 0.999 | 1.244** | 1.061* |
| | (1.49) | (2.14) | (1.93) |
| *R&D intensity (t-1)* | -0.764 | 0.017 | -0.049 |
| | (-1.01) | (0.04) | (-0.11) |
| *R&D intensity (t-2)* | 0.468 | 0.907 | 0.868 |
| | (0.39) | (0.97) | (0.98) |
| Industry×Year FE | No | Yes | Yes |
| CPC×Year FE | Yes | No | Yes |
| Observations | 1,587,681 | 1,587,686 | 1,587,681 |
| Pseudo $R^2$ | 0.266 | 0.517 | 0.530 |

**Table IA5. Market Value of AI Patents**

This table examines the market value premium of AI patents relative to non-AI patents using fixed-effect Poisson regression model. The dependent variable, Patent Value, is defined as the patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). The main independent variable, AI Patents, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, as defined by the Artificial Intelligence Patent Dataset (AIPD). Firm×Year fixed effects are also included. Standard errors are clustered by the patent grant year-firm, and z-statistics are reported in parentheses. All variables are winsorized at the top and bottom 1 percent of the cross-sectional distribution and defined as outlined in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10 percent, 5 percent, and 1 percent, respectively.

| **D.V.: Patent Value** | (1) |
|---|---|
| *AI Patent* | 0.004** |
| | (2.14) |
| Industry×Year FE | No |
| CPC×Year FE | No |
| Firm×Year FE | Yes |
| Observations | 1,582,696 |
| Pseudo $R^2$ | 0.818 |

**Table IA6. AI Innovation and Accounting Performance: Asset Turnover and Sales-to-Employees**
This table examines the effects of AI innovation on Asset Turnover and Sales-to-Employees over the three years following patent grants. Sales-to-Employees is constructed using actual resume data from Revelio to measure employment levels, while sales data is sourced from firms' financial statements in Compustat. The accounting metrics are evaluated one year after the patent grant (Column 1), two years post-grant (Column 2), and three years post-grant (Column 3). The sample includes firms that have at least three years of forward data for the dependent variable. Panel A, reports the analysis with asset turnover as the dependent variable. Panel B, reports the analysis with sales-to-employees as the dependent variable. The independent variables include the market value-weighted sum of AI patents and all granted patents, calculated using the market value as weights and log-transformed (log + 1). Control variables include R&D Intensity, Capital Intensity, Intangible Assets Intensity, Firm Size, and Book-to-Market Ratio. Firm and Year fixed effects are included in all models. All variables are winsorized at the 1% and 99% levels and standardized to zero mean and unit standard deviation. Standard errors are double-clustered by firm and fiscal year, and t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

**Panel A. Asset Turnover**

| **D.V.: Asset Turnover** | (1)<br>Forward 1 year | (2)<br>Forward 2 years | (3)<br>Forward 3 years |
|---|---|---|---|
| *Value of AI Patents* | 0.001 | 0.003 | 0.003 |
| | (0.31) | (0.69) | (0.73) |
| *Value of Patents* | -0.012** | -0.010** | -0.008* |
| | (-2.68) | (-2.35) | (-1.81) |
| *R&D Intensity* | 0.004 | 0.009** | 0.011*** |
| | (0.94) | (2.10) | (2.91) |
| *Capital Intensity* | 0.004 | -0.010*** | -0.014*** |
| | (1.14) | (-3.03) | (-4.51) |
| *Intangible Assets Intensity* | -0.087*** | -0.068*** | -0.051*** |
| | (-15.44) | (-12.98) | (-8.96) |
| *Firm Size* | 0.083*** | 0.002 | -0.022 |
| | (3.33) | (0.09) | (-0.95) |
| *Book-to-Market Ratio* | -0.050*** | -0.016** | 0.003 |
| | (-5.09) | (-2.81) | (0.95) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 51,072 | 51,072 | 51,072 |
| Adjusted $R^2$ | 0.897 | 0.895 | 0.893 |

**Panel B. Sales-to-Employee**

| **D.V.: Sales-to-Employee** | (1)<br>Forward 1 year | (2)<br>Forward 2 years | (3)<br>Forward 3 years |
|---|---|---|---|
| *Value of AI Patents* | 0.029 | 0.031 | 0.029** |
| | (0.76) | (1.03) | (2.09) |
| *Value of Patents* | -0.070 | -0.041 | -0.048 |
| | (-1.48) | (-0.94) | (-1.37) |
| *R&D Intensity* | 0.021 | 0.017 | 0.016 |

| | | | |
|---|---|---|---|
| | (0.86) | (0.97) | (1.05) |
| *Capital Intensity* | 0.030 | 0.029 | 0.034 |
| | (0.94) | (0.98) | (1.19) |
| *Intangible Assets Intensity* | 0.002 | 0.025 | 0.031 |
| | (0.08) | (0.91) | (1.24) |
| *Firm Size* | $0.962^{***}$ | $0.664^{***}$ | $0.481^{**}$ |
| | (4.96) | (3.48) | (2.79) |
| *Book-to-Market Ratio* | $-0.134^{**}$ | $-0.148^{**}$ | $-0.155^{***}$ |
| | (-2.29) | (-2.51) | (-3.02) |
| Firm FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 26,078 | 26,078 | 26,078 |
| Adjusted $R^2$ | 0.870 | 0.887 | 0.889 |

**Table IA7. AI Innovation and Market Concentration**

This table examines the effects of AI innovation on market concentration (measured by HHI at the SIC3 level) over the three years following patent grants. The sample includes firms that have at least three years of forward data for the dependent variable. Panel A evaluates the impact across all industries, and Panel B focuses on the top 25 percent most concentrated industries. The dependent variable, HHI, is evaluated one year after the patent grant (Column 1), two years post-grant (Column 2), and three years post-grant (Column 3). The independent variables include the log-transformed (log + 1) market value-weighted sum of AI patents and all granted patents, aggregated by industry. Control variables, including R&D Intensity, Capital Intensity, Intangible Assets Intensity, Firm Size, and Book-to-Market Ratio, are averaged within each SIC3 by market value weights, with firm size calculated as the sum of all firms within each SIC3. Firm and Year fixed effects are included in all models. Standard errors are double-clustered by industry and fiscal year, and t-statistics are reported in parentheses. All variables are winsorized at the 1 percent and 99 percent levels and standardized to zero mean and unit standard deviation. Coefficients marked with *, **, and *** are significant at 10 percent, 5 percent, and 1 percent, respectively.

**Panel A. All industries**

| **D.V.: HHI** | (1)<br>Forward 1 year | (2)<br>Forward 2 years | (3)<br>Forward 3 years |
|---|---|---|---|
| *Value of AI Patents* | 0.004 | -0.002 | -0.007 |
| | (0.73) | (-0.41) | (-1.11) |
| *Value of Patents* | 0.004 | 0.007 | 0.008 |
| | (0.43) | (0.68) | (0.83) |
| *R&D Intensity* | -0.006 | -0.003 | -0.002 |
| | (-0.58) | (-0.29) | (-0.19) |
| *Capital Intensity* | -0.011* | -0.012** | -0.011* |
| | (-1.91) | (-2.14) | (-1.83) |
| *Intangible Assets Intensity* | 0.000 | -0.000 | -0.005 |
| | (0.01) | (-0.05) | (-0.55) |
| *Firm Size* | -0.028* | -0.019 | -0.015 |
| | (-1.79) | (-1.31) | (-1.02) |
| *Book-to-Market Ratio* | 0.005 | 0.004 | 0.001 |
| | (0.92) | (0.73) | (0.11) |
| Industry FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 4,798 | 4,798 | 4,798 |
| Adjusted $R^2$ | 0.820 | 0.823 | 0.823 |

**Panel B. Top 25 Percent Concentrated Industries**

| **D.V.: HHI** | (1)<br>Forward 1 year | (2)<br>Forward 2 years | (3)<br>Forward 3 years |
|---|---|---|---|
| *Value of AI Patents* | -0.007 | -0.028 | -0.049** |
| | (-0.39) | (-1.54) | (-2.49) |
| *Value of Patents* | 0.011 | 0.014 | 0.027 |
| | (0.46) | (0.66) | (1.07) |
| *R&D Intensity* | 0.024 | 0.035 | 0.040* |
| | (1.14) | (1.65) | (1.96) |
| *Capital Intensity* | -0.007 | -0.008 | -0.006 |
| | (-1.24) | (-1.14) | (-0.77) |

| | | | |
|---|---|---|---|
| *Intangible Assets Intensity* | 0.008 | 0.000 | -0.008 |
| | (0.66) | (0.03) | (-0.53) |
| *Firm Size* | -0.020 | 0.003 | 0.006 |
| | (-1.15) | (0.16) | (0.30) |
| *Book-to-Market Ratio* | -0.001 | 0.003 | -0.002 |
| | (-0.16) | (0.34) | (-0.24) |
| Industry FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |
| Observations | 1,081 | 1,081 | 1,081 |
| Adjusted $R^2$ | 0.617 | 0.628 | 0.648 |