The Value of AI Innovations in non-IT Firms*

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Abstract

Motivated by the recent widespread diffusion of AI technologies into the application sectors of AI (or non-IT industries), we examine the profile of non-IT firms engaging in AI innovation and the value implications of these innovations. AI innovations in non-IT industries are concentrated in a small subset of firms that were also active innovators in non-AI technologies with lower market share of sales before engaging in AI innovations for the first time. We also find that investors value AI innovations more than others, as AI patents exhibit a 6% value premium compared to the same patent classification and industry group. Innovation spillovers associated with AI technologies, and the improvements in the competitive position for firms that are engaging in AI innovation likely explain the value premium of these innovations, as we find that AI innovation is associated with more forward citations and increases in the market share of sales.

Keywords: Artificial Intelligence, Innovation, Valuation

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1 Introduction

First invented in the computer science domain, in recent years, application of AI technologies has been widely developed across a wide range of sectors throughout the rest of the economy (see Figure 1). From self-driving vehicles, to chatbots, to AI-driven enhancement to production processes, there are numerous examples of innovations of AI technologies in the non-IT industries that apply and integrate AI technologies into business operations. Figure 2 illustrates the growing trend of AI innovations in these industries, showing that innovation in AI has increased dramatically from 7% of all innovations in 2001 to 23% of all innovations in 2023. Motivated by this trend, we investigate the profile of firms that develop AI technologies in these industries and study the market assessment of the value of these technologies.

Our analysis of these research questions is also motivated by the large potential benefits at stake for developing AI technologies for non-IT firms. As a general-purpose technology, AI is expected to have wide-ranging applications that can drive growth and innovation development in application (non-IT) sectors as it continues to develop and mature over time (Bresnahan and Trajtenberg, 1993). On the other hand, there are significant challenges in the development of AI technologies, particularly in the application, non-IT sectors. These technologies are characterized by long development lags, as the core technologies are continuously developed and refined downstream for specific applications (Bresnahan, 2010), leading to high costs and uncertainty in its development trajectory. Moreover, effective development of AI in the application sector relies on the combination of the knowledge in the new AI technology and the industry-specific knowledge in the application sector. Taken together, these factors give rise to specialization in the development of these technologies, and also opens empirical questions on the value of these innovations of AI in non-IT sectors.

We begin our analysis by studying 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 a concentrated subset of firms is increasingly 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. Moreover, we analyze the determinants of AI patenting activity, and we find that the prior 5-year stock of AI patenting activity is strongly associated with the number of AI patents, which provide further evidence of specialization in the development of AI technologies.

As we find that AI patenting activity is concentrated in a small subset of firms, we further investigate the factors that are associated with the *initiation* of AI patenting 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 the prior stock of non-AI patents and software patents are positively associated with the incidence of the first AI patenting activity. Moreover, we find that firms with lower market share of sales 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 both the software and the non-IT domains, and the firms' competitive position, are important factors that drive non-IT firms to engage in AI innovations.

Next we study the market assessment of the value of AI patents.[1] 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

[1] 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.

to as the value premium of AI innovations). Our analysis shows that AI patents are roughly 6% more valuable compared to non-AI patents, and after controlling for firm-year fixed effects, we continue to find that AI patents are modestly more valuable compared to non-AI patents.[2]

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 for firms that exhibit high AI potential (as measured by the Felten et al, 2021 index on AI exposure), these firms exhibit a 32% 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

[2] 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.

(Hall et al, 2005; Kogan et al, 2017), 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% more compared to non-AI patents. Moreover, we also find that AI patents are cited by other patents in the same technology class by around 10% more compared to non-AI patents, suggesting that AI patents are cutting edge technologies that spur other innovations in the same technology class.

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 investigate 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 gross margins in the 1–3-year horizon. Moreover, we also find some evidence of improvements in the worker productivity, as we find that sales-to-employees increases over the 1–3-year horizon for firms that invest more in AI patents.

In addition, we further show that the gross margins and the worker productivity improvements in firms that engage in AI innovations, also improve their competitive position. Specifically, we find that firms that engage in more AI patenting enjoy an increase in the market share of sales over the 1–3-year horizon. Moreover, at the industry-level, we also uncover further evidence that this increase in market share has implications for industry-wide competitive dynamics, as we find that for highly concentrated industries, the extent of AI patenting is associated with a decrease in the sales-based Herfindahl index at the 2- and 3-year horizons.

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, and we find that these patents are more highly valued by investors compared to other patents.

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, and we show that these investments are associated with improvements in the competition position of firms and are also highly valued by investors.

Third, we also contribute to recent studies that examine the changes in market power and market concentration in the economy. Notably, scholars have argued that market dominant firms are increasing their market power over the past few decades (Gutiérrez and Philippon, 2018), and some argue that the rising dominance of these firms can be attributed to the emergence of new, automating technologies (Autor et al, 2017; Autor et al, 2020). Thus the insights from this literature suggest that the adoption of AI should enable market leaders to extend their dominance. In contrast to this prediction, our findings show that while AI innovations are associated with improvements in market share, the firms that initiate investment in AI innovations are not the market leaders. Consequently, we find some evidence that AI innovations lead to greater market competition in industries with high concentration.

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" including some GPTs, 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 particularly 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 could drive operational gains in a broad set of firms in the economy.

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 prior literature on AI and GPTs, 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 in these types of 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 AI 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 technologies (Tambe et al, 2021). As AI is a subset of digital technologies, we expect an accumulation of AI knowledge in certain firms that frequently innovate in AI technologies as well. This leads to the prediction that firms with greater prior knowledge of AI technologies will tend to invest in more AI technologies. Thus, we examine the following hypothesis:

H1a: Existing knowledge in AI 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: Existing 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 technologies, as these are technologies that have been an innovation focus for many companies 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 are often characterized by 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 1970s and 1980s 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. Recent work by 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 technologies when they are being developed.

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.

Consequently, we hold no ex-ante expectations on whether there exists a value premium of AI innovation, or put differently, whether AI patents would be more highly valued compared to other patents. 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 stems 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, leads to the prediction that AI technologies in the non-IT sector should exhibit a gradual increase in value over time, 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). Consequently, we expect that these breakthrough events that increased the technical capabilities of AI should play an important role in driving the value of AI innovations:

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

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 have been used to 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 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). 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.[3][4]

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.

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

[3] 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.

[4] 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.

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. 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 1, 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.

As our study focuses on the AI patenting activity in the non-IT sectors, we present additional statistics in Figure 2 that depicts the overall trends in AI innovation in these sectors. At the beginning of our sample period, AI patents granted to public firms were relatively scarce, comprising only about 3700 per year, which represented a modest 7% of the total patents issued. In the following years, we observe a consistent annual growth at an average rate of 6%, culminating in the issuance of over 17,000 AI patents in the year 2022. Notably, AI patents have become increasingly prominent, representing about 23% of the total patents granted to public non-IT companies. This trend underscores the rising significance and proliferation of AI technology in non-IT firms.

Moreover, in Figure 3, we further explore the increase in AI patenting activity 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.

Next, Table 1 examines the industry distribution of AI patents categorized by 2-digit SIC major groups. 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).[5]

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% 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

4.2.1 Determinant Factors Associated with AI Patenting Activity

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

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

where the dependent variable, $\# \ of \ Patents_{it}$, represents the number of AI patents applied for by firm i in year t, which captures the firm-level innovation activity in AI technologies. The

[5] For simplicity, the results in Table 1 are presented based on the 2-digit SIC code.

key explanatory variable is $Log(Value\ of\ AI\ Patents_{it})$, which measures the logarithm of the cumulative stock of AI patents held by the firm weighted by their market value. This variable reflects the firm's accumulated knowledge and technological capabilities in AI-related areas. Additionally, $Log(Value\ of\ \ Patents_{it})$, the logarithm of the value of all patents granted to the firm is also a proxy for general domain knowledge of a 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 $Log(Firm\ Size_{it})$, the natural logarithm of net sales and $R\&D\ Intensity_{it}$, the R&D expenditures to total assets. We also include $Sales\ Growth_{it}$, the annual growth in sales, as well as $Leverage_{it}$ (the ratio of total debt to total assets) and $External\ Finance_{it}$ (the ratio of net external financing to total assets) to control for the firm's financial health and access to funding. Additionally, we also control the firms' fixed assets investment with $Capital\ Intensity_{it}$, the ratio of capital expenditures to total assets, and we also include the logarithm of firm age (Age_{it}). Lastly, we include measures of market competition with $Sales\ Share_{it}$, the market share of sales, which represents the firm's competitive position within its industry, and HHI_{it}, which measures the sales-based industry concentration.

We report the results of this determinant analysis in Table 3. Notably, across all specifications, the coefficient on value of AI patents stock is consistently positive and statistically significant. This indicates that firms with a higher stock of AI patents tend to develop more AI patents over time, supporting the *H1a* that posits that prior investments in AI innovation create cumulative advantages. 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).

Specifically, in the first set of results in column (1) of Table 3, which does not include fixed effects, our analysis suggests that an additional million dollars in the stock of AI patents is associated with a 60% increase in the number of AI patents developed by the firm. Column (2) introduces year and industry fixed effects, and the coefficient on value of AI patents stock remains positive and statistically significant, suggesting that the observed relationship is robust to changes in the overall technological landscape over time and industries. The analysis in Column (3) which includes industry-year fixed effects also finds that the value of AI patents stock is positive and significantly related to AI patenting activity, which highlights that firms leading in AI innovation continue to do so even when accounting for industry-level dynamics and temporal changes.

Across all specifications, we also find that R&D intensity is strongly positive and significant, supporting the idea that firms with higher investments in R&D are more likely to develop AI innovations. 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). Moreover, sales growth shows a significantly negative coefficient across all specifications. This suggests that firms experiencing weaker sales growth 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.

4.2.1 Determinant Factors of Initial AI Innovation

In this analysis, we examine the factors that are associated with the initial patenting activity. Our analysis is motivated by a tension highlighted in our discussion of *H1a*. 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).

To empirically test the hypothesis regarding the role of existing knowledge in non-AI technologies in fostering AI innovation (*H1b*), we estimate Equation (1) with several modifications to the regression model. First, we modify the dependent variable in Equation (1) to an indicator equal to 1 for the firm's first AI patent and 0 otherwise. Additionally, in this analysis of the initial AI patenting activity, we study two different sets of domain knowledge that could increase the likelihood of engaging in AI innovations for the first time. Specifically, we examine the cumulative stock of non-AI patents held by the firm weighted by their value, $Log(Value\ of\ NonAI\ \ Patents_{it})$, and the cumulative stock of all software patents held by the firm weighted by their market value, $Log(Value\ of\ Software\ Patents_{it})$.

We present the determinants of the initial AI patenting activity in Table 3, Panel B and the panel is structured in the following way: Column (1) uses a logit regression as a baseline. Column (2) employs linear regression without fixed effects, while Column (4) includes industry and year fixed effects, and Column (5) incorporates industry-year fixed effects to account for industry-specific trends over time.

Across all specifications, the coefficient on the value of non-AI patents stock is positive and highly significant, suggesting that firms with greater stocks of innovation in non-AI technologies are more likely to innovate in AI. This finding supports the notion that existing knowledge in non-AI technologies complements AI technology development and facilitates entry into the AI domain. For instance, in Column (2)-(4), a 1% increase in the value of non-AI patent stock corresponds to about 4.5% increase in the probability of developing AI technologies. This relationship persists across all specifications, underscoring the robustness of the finding. 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.

Coefficients on the value of software patents stock is also positive and significant in all specifications, highlighting the importance of spillovers from software technologies. Firms with stronger software portfolios face fewer barriers to entering the AI domain, as these technologies are closely related. For example, in Column (2)-(4), a 1% increase in the value of software patents stock is associated with about 10% increase in the likelihood of developing AI technologies. These results further underline the role of complementary technological capabilities in facilitating early AI innovation.

Moreover, we also find that the coefficient on market share is negative and significant across all columns. This suggests that firms with smaller market shares are more likely to pursue AI innovation, potentially as a strategic move to leverage the competitive advantages offered by these technologies and improve their market positioning. Similarly, the negative and significant coefficient on sales growth aligned with the results observed previously, suggesting that firms experiencing weaker sales growth are more inclined to engage in AI innovation. Thus, these patterns suggest that firms with competitive or growth challenges may view AI innovations as a strategic opportunity to reposition themselves in the market.

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:

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

The dependent variable ($Patent\ Value_{ijt}$) 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).[6] $AI\ Patent_{ijt}$ 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 β_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.[7]

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 ($Industry \times Year\ FE$).[8] 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 ($Log\ Firm\ Size_{jt}$), the log-transformed return volatility (Log $RetVol_{jt}$). Additionally, we control for the research input costs, with the R&D intensity ($R\&D\ Intensity_{jt}$), as well as the lagged values of R&D intensity $R\&D\ Intensity_{jt-1}$ and $R\&D\ Intensity_{jt-2}$. 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

[6] 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.

[7] 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.

[8] The CPC is the latest patent classification scheme that is jointly used by the USPTO and the EPO.

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.[9][10] Specifically, in Column (1), which includes industry-year fixed effects, the analysis shows that AI patents are, on average, 13.7% more valuable than non-AI patents within each year and industry. Column (2) incorporates CPC-year fixed effects, and our analysis suggests that AI patents are 19.6% more valuable within each technology class and year. Column (3) includes both CPC-year and industry-year fixed effects, showing that within each industry, CPC group, and year, AI patents are 6.6% more valuable than non-AI patents. Finally, Column (4) uses firm-year fixed effects, providing the most stringent controls by examining variations within each firm-year.[11] Under this specification,

[9] 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 IA3, 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% and 50%), as specified by the AIPD. The results, reported in Table IA4, are consistently positive and significant across all specifications, underscoring the robustness of our findings.

[10] In additional analyses, we investigate whether the incremental value of AI patents is concentrated among firms with high levels of prior innovation activity. Table IA2 presents an analysis where firms are categorized based on their stock of innovation over the past five years. In Panel A, firms are divided into the top 25% and bottom 75% based on total patent stock. The results show that the value premium of AI patents is significant only among the top 25% of firms, indicating that firms with substantial prior innovation portfolios derive the most value from AI patents. In Panel B, firms are categorized based on their AI patent stock, and the results similarly show a significant value premium for AI patents only among firms in the top 25%. These findings suggest that the incremental value of AI patents is concentrated in firms with strong prior innovation activity, particularly in AI-related technologies. Moreover, these results suggest that firms with higher prior innovation activity, particularly in AI, are better equipped to capitalize on the potential of AI innovations, which aligns with the "superstar firms" effect, where a small subset of firms with substantial technological and organizational resources disproportionately benefit from new innovations (Autor et al., 2017; Ayyagari et al., 2023).

[11] We note that 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.

AI patents are, on average, 0.4% more valuable than non-AI patents, indicating that even within firms, AI patents add incremental value.[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.

4.4 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.

[12] In Figure IA1, 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% within CPC-year fixed effects and more than 10% 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.

[13] 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, 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.

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:

$$Patent\ Value_{ijt} = \alpha + \beta_1 Post\ AlexNet_t \times High\ AI\ Potential_j + \beta_2 Log\ Firm\ Size_{jt} + \beta_3 Log\ RetVol_{jt} + \beta_4\ \ R\&D\ Intensity_{jt} + \beta_5 R\&D\ Intensity_{jt-1} + \beta_6 R\&D\ Intensity_{jt-2} + CPC \times Month\ FE\ + Firm\ FE + \varepsilon_i \tag{3}$$

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

Our results of this analysis are presented in Table 5. Consistent with *H3a*, we find that the introduction of AlexNet is associated with a significant 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% 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, with AI patents granted post-AlexNet being 37.5% more valuable in firms with greater AI potential compared to other firms. These findings align with our expectations that breakthroughs, such as AlexNet, which enhance AI's technical capabilities, play a critical 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 model 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 6, Panel A, provide strong evidence that AI patents receive significantly more forward citations than non-AI patents across all specifications. This finding supports 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.

Specifically, in Column (1) of Table 6, Panel A, which includes industry-year fixed effects, AI patents receive 34.8% more forward citations than non-AI patents, highlighting the broader influence of AI technologies within industries over time. Column (2), which includes CPC group-year fixed effects, shows that AI patents receive 25.6% more forward citations, indicating that even within technology classes, AI patents exhibit significantly higher quality and innovation spillover potential. In Column (3), which combines both industry-year and CPC group-year fixed effects, AI patents still receive 22.4% more forward citations, underscoring the robustness of this relationship when accounting for both industry and technological trends. Finally, in Column (4), with the inclusion of firm-year fixed effects, AI patents receive 29.6% more forward citations than non-AI patents, further confirming their ability to spur innovations even when controlling for firm-specific factors and within-technology variation.[14]

In Table 6, 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. For example, in Column (3), which includes industry-year fixed effects, AI patents receive 27.8% more within-CPC group citations compared to non-AI patents. This further underscores the superior quality of AI innovations and their greater ability to spur follow-on innovations within the same technological domain.

[14] 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.

4.4.2 Competitive Advantages of AI Innovations

The second hypothesis regarding the drivers of the value premium of AI innovations (*H4*) suggests that these innovations improve the firm's competitive position by increasing efficiency in production and 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:

$$y_{it} = \alpha + \beta_1 Log(Value\ of\ AI\ Patents\ Stock_{it}) + \beta_2 Log(Value\ of\ Patents\ Stock_{it}) + \beta_3 R\&D\ Intensity_{it} + \beta_4\ Capital\ Intensity_{it} + \beta_5\ Intangibles\ Intensity_{it} + +\beta_6 Log(Firm\ Size_{it}) + \beta_7 BooktoMarket_{it} + Firm\ FE + Year\ FE + \epsilon_{it} \quad (4)$$

where y_{it} represents various accounting performance metrics for firm i in year t, including return on sales (ROS), gross margins, asset turnover, employees-to-sales ratios, and sales-based market share which proxy for the firm's competitive positioning and operational efficiency.

The main independent variable in Equation (4) is $Log(Value\ of\ AI\ Patents\ Stock_{it})$, which measures the cumulative stock of AI patents held by the firm weighted by their market value. As a control, we also include, $Log(Value\ of\ Patents\ Stock_{it})$, the cumulative stock of all patents held by the firm weighted by their market value, 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 total 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 7 reports the effects of AI innovation on return on sales (ROS) and gross margins. Panel A focuses on ROS, showing a positive and significant impact of value of AI patents one and two years after patent grants, even after controlling for firm characteristics and incorporating firm and year fixed effects. This finding supports the hypothesis that AI innovations improve production efficiencies and facilitate product innovation, which subsequently enhances firm profitability. Panel B extends this analysis to gross margins, where the value of AI patents has a positive and significant impact across all horizons (one to three years post-patent grant). 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.

Focusing more on the efficiency channel, Table 8 examines the effects of AI innovations on asset turnover and employee-to-sales ratios. Panel A, which investigates asset turnover, shows no significant impact of AI innovations across all horizons. However, Panel B reveals a positive and significant impact on employee-to-sales ratios in the one, two, and three years after patent grants. This finding indicates that AI innovations improve labor efficiency, allowing firms to generate more revenue per employee. These results suggest that while AI may not immediately enhance overall asset efficiency, it significantly improves operational efficiency by optimizing workforce productivity.

Given these improvements in firm performance, 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. Table 9 presents results with market share as the dependent variable. Consistent with 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 10% increase in value of AI patents is associated with a 0.04% increase in market share. These results therefore reinforce the notion that AI innovations not only improve internal efficiency but also translate into tangible competitive gains for firms.

To explore the broader industry-level implications of AI innovations, we aggregate the data at the industry level and estimate Equation (4) with the Herfindahl-Hirschman Index (HHI) at the industry level as the dependent variable. Table 10 presents the results. Panel A, which examines all industries, shows no significant impact of AI innovations on market concentration. However, in Panel B, which focuses on the top 25% most concentrated industries, AI innovations are significantly associated with a reduction in market concentration in the two and three years post-patent grant. These results suggest that AI innovations could enhance competition in highly concentrated industries by enabling firms to gain market share and to challenge market leaders.

Combining this finding with the earlier results on firm-level market share (Table 9), we demonstrate that while AI innovations increase market share for innovating firms, they also appear to reduce concentration in highly concentrated industries. This indicates that AI technologies may act as a competitive equalizer, allowing firms with innovative capabilities to challenge dominant players and to reshuffle market dynamics. Moreover, our firm-level results also highlight the diverse ways in which AI innovations confer competitive advantages to firms. By facilitating product innovation, improving production and operating efficiencies, AI patents contribute to enhanced firm performance metrics, such as higher profitability (ROS and gross margins) and greater labor efficiency (employee-to-sales ratios).

5 Conclusion

General purpose technologies, such as AI, have driven widespread and sustained periods of growth throughout economic history. Consequently, the recent development of AI has led many to speculate on the large potential value of these technologies as they continue to be integrated into application sectors or non-IT industries. Thus, in this study, we analyze the drivers and value implications of AI innovation as it diffuses across non-IT firms.

Over time, we find that a concentrated subset 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, also tend to be active innovators in non-AI innovations, suggesting that prior non-IT industry knowledge in innovation complements the development of AI technologies in non-IT firms.

Consistent with the large and widespread economic benefits that have been predicted by economists (i.e. Brynjolfsson et al, 2019), we find that AI patents are more valued than other types of innovations in the same patent classification and industry group by 6%. 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 by more than 30%. 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, gross margins, work productivity, and market share.

Taken together, our findings provide important practitioner insights on the value of AI technologies. Specifically, we find a value premium in AI innovations, due to the knowledge spillovers and market competition advantages of AI. Moreover, we provide further insight on the industry competitive dynamics of AI adoption, as we find that concentrated industries with a greater extent of AI innovations tend to exhibit an increase in market competition.

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Appendix A: Variable definitions

Variables	Definitions
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.
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 (Firm)	An indicator variable equal to 1 for patents assigned to firms in the top 10% 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.
Gross Margin	The ratio of gross profit to total sales.
Employee-to-sales	The ratio of total employees 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 Stock	The natural logarithm of 1 plus the weighted average of granted AI patents stock, 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, 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, where the weight is determined by the market value of AI patents.

Log Value of Patents Stock	The natural logarithm of 1 plus the weighted average of all granted patents stock, where the weight is determined by the market value of granted patents.

Figure 1. 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).

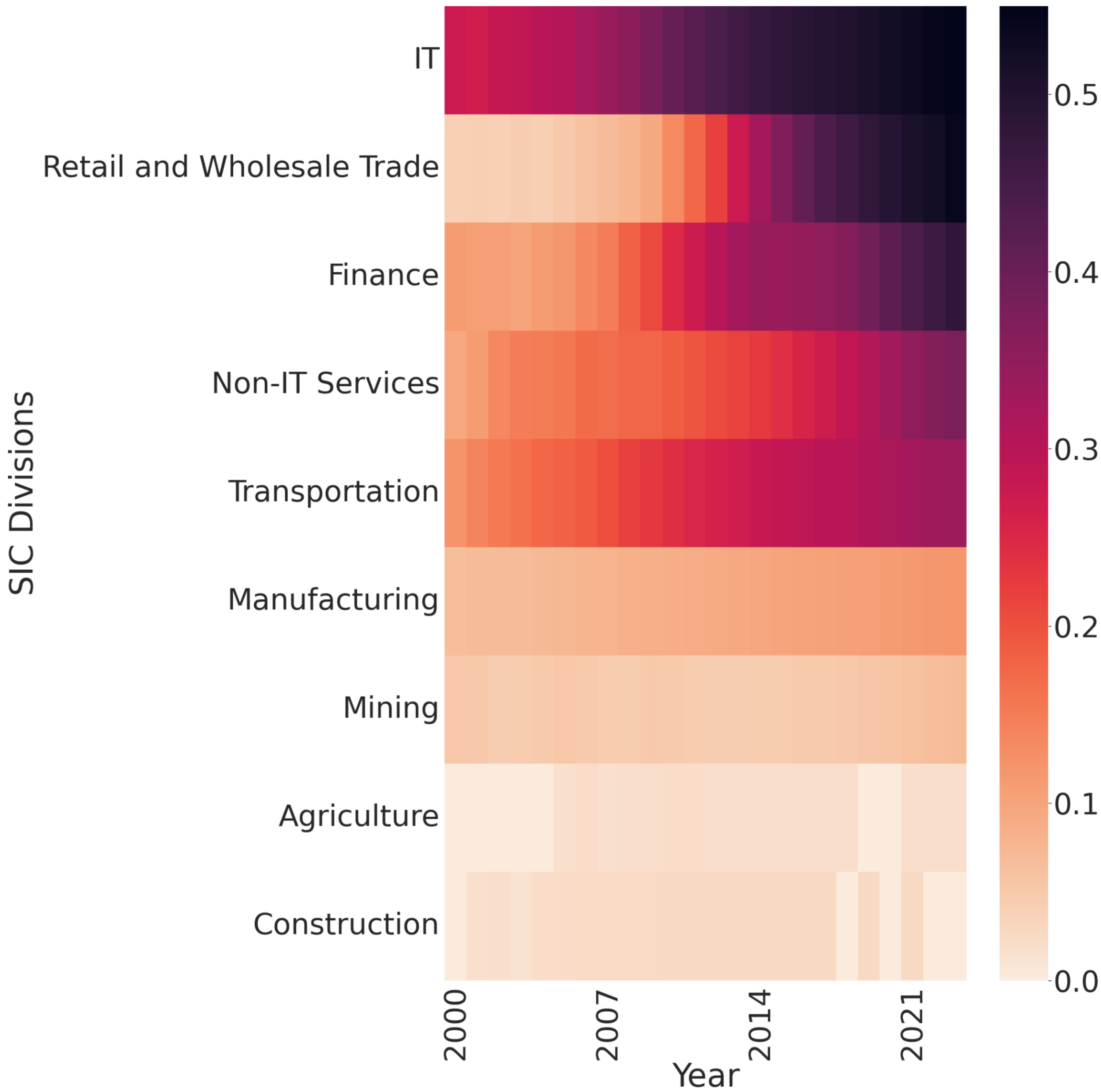

Figure 2. Time Trends of AI Innovation

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.

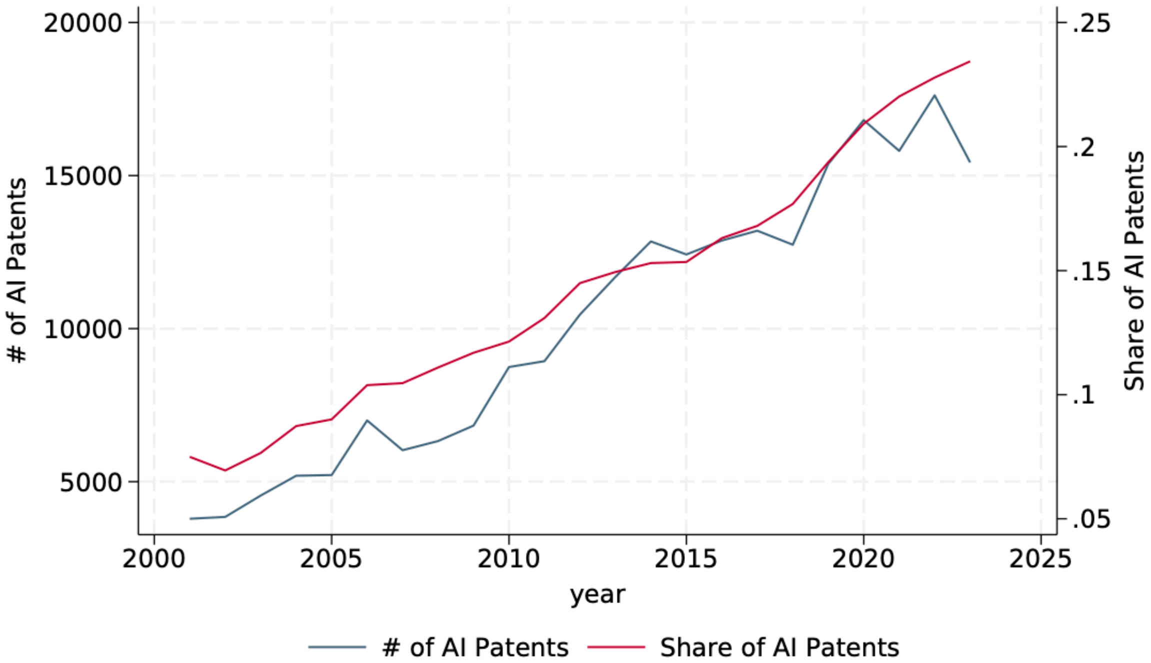

Figure 3. Intensive Margin and Extensive Margin of AI Innovation by Years

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).

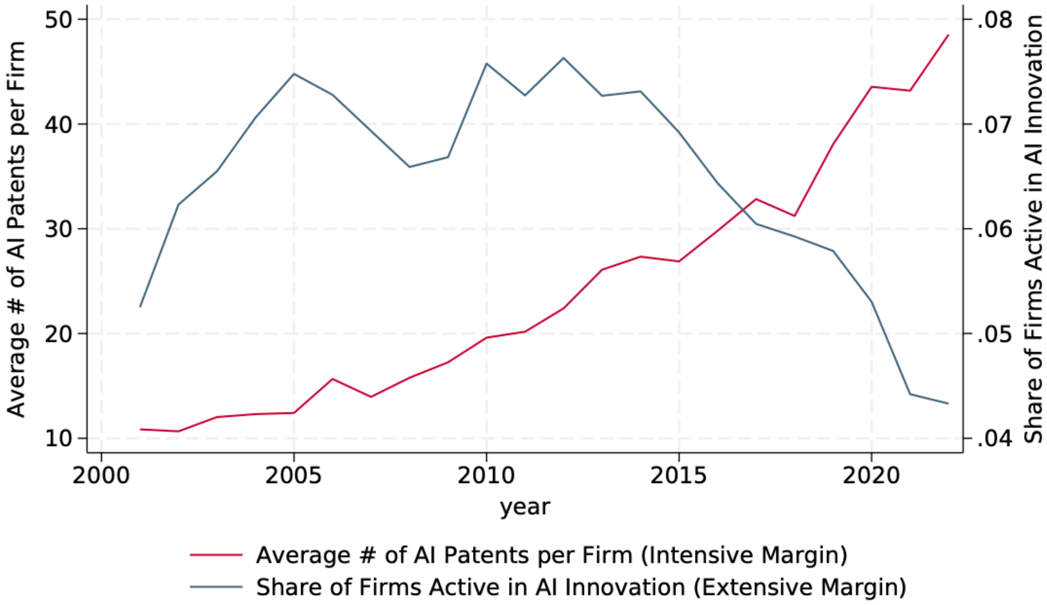

Figure 4. Parallel Trends: AI Patents Market Value Around the Introduction of AlexNet
This figure illustrates the estimated γ^k values from Equation (4) for the period centered on AlexNet's introduction in September 2012. These values capture the evolving impact of AlexNet on the market value of AI patents 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% confidence intervals. A vertical red dashed line denotes the initial release of AlexNet for clarity.

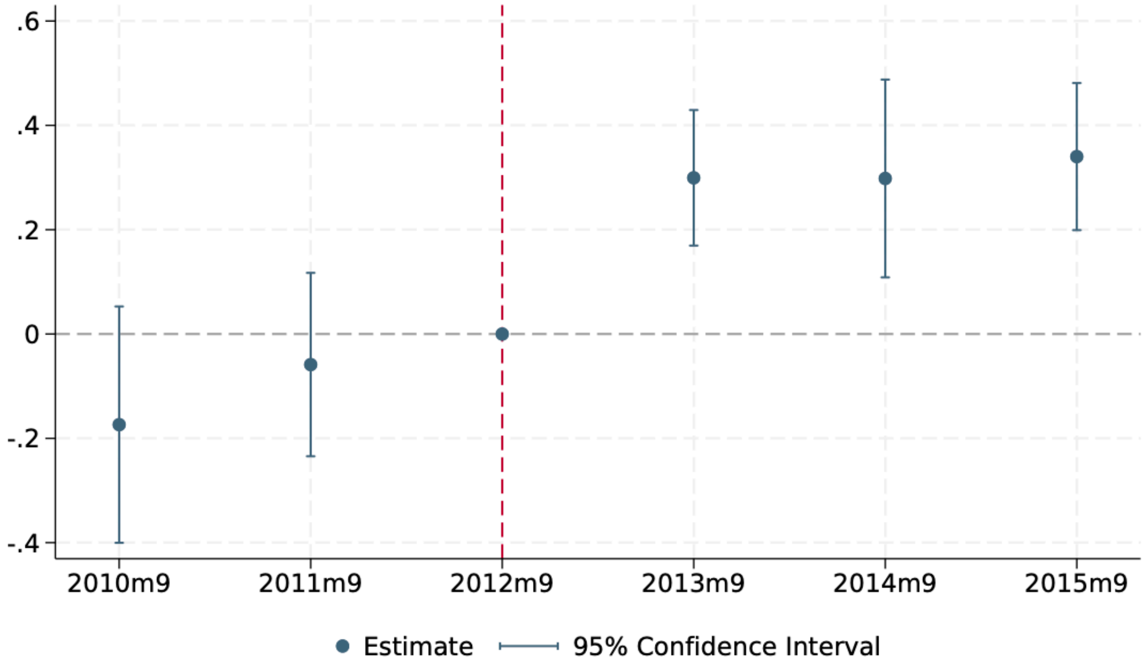

Table 1. AI Patenting Across Industries

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	68,224	0.030	0.216	-0.011	0.043	0.105
Asset Turnover	68,224	0.941	0.742	0.410	0.762	1.258
Gross Margin	68,224	0.391	0.229	0.226	0.363	0.544
Employee-to-sales	67,130	0.005	0.005	0.002	0.003	0.006
Market Share	68,224	0.066	0.156	0.001	0.007	0.045
HHI	68,224	0.193	0.186	0.064	0.129	0.253
Book-to-market	68,224	0.758	0.763	0.316	0.561	0.927
Capital Intensity	68,224	0.049	0.066	0.010	0.028	0.061
R&D Intensity	68,224	0.030	0.063	0.000	0.000	0.028
Intangible Asset Intensity	68,224	0.184	0.242	0.005	0.077	0.284
Firm Size (Sales)	68,224	3.981	11.262	0.125	0.549	2.312
Sales Growth	68,224	0.086	0.350	-0.032	0.066	0.180
Leverage	68,224	0.254	0.334	0.033	0.186	0.404
External Finance	68,224	0.043	0.283	-0.032	0.000	0.038
Age	68,224	18.500	15.248	7.000	15.000	26.000
High AI Exposure (Firm)	28,350	0.497	0.500	0.000	0.000	1.000
Value of AI Patents Stock	68,224	28.069	328.388	0.000	0.000	0.000
Value of Non-AI Patents Stock	68,224	140.008	914.390	0.000	0.000	0.042
Value of Software Patents Stock	68,224	10.380	112.480	0.000	0.000	0.000
Value of Patents Stock	68,224	172.257	1,187.721	0.000	0.000	0.276

Table 3. Determinants of AI Innovation

This table reports the determinant analysis of AI innovation. Panel A focuses on the number of AI patents, while Panel B examines the determinants of a firm conducting its first AI innovation. The dependent variable in Panel A is the number of AI patents applied for in a given year, and all models use fixed-effect Poisson regression models. The dependent variable in Panel B is a binary indicator for whether the firm applies for its first AI patent. Column (1) in Panel B uses a logistic regression model, while Columns (2)–(4) use linear regression models with multi-way fixed effects. Value of Patents Stock (AI/NonAI/Software/All) is the natural logarithm of 1 plus the market value-weighted stock of AI/NonAI/Software/All patents granted to the firm. Standard errors are double-clustered by the firm and year, and t-statistics or z-statistics are reported in parentheses. The unit of observation is at the firm-year level, and patenting activity is measured using application dates within a given year. All variables are winsorized at the top and bottom 1% of the cross-sectional distribution. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

Panel A. Number of AI Patents

D.V.: Number of AI Patents	(1)	(2)	(3)
Value of AI Patents Stock	0.566***	0.478***	0.470***
	(10.10)	(7.36)	(7.30)
Value of Patents Stock	0.043	-0.030	-0.021
	(0.95)	(-0.57)	(-0.38)
R&D Intensity	5.919***	3.373***	3.998***
	(5.95)	(4.20)	(4.82)
Firm Size	0.393***	0.462***	0.475***
	(4.58)	(5.04)	(5.00)
Sales Growth	-0.881***	-0.970***	-0.917***
	(-4.19)	(-5.96)	(-5.23)
Leverage	0.086***	0.119***	0.617
	(4.98)	(4.04)	(1.15)
External Finance	-0.011	0.247*	0.076
	(-0.06)	(1.84)	(0.51)
Capital Intensity	1.118	0.671	1.062
	(0.66)	(0.57)	(0.85)
Age	-0.000	0.001	-0.000
	(-0.08)	(0.15)	(-0.07)
Market Share	-0.743	0.349	0.329
	(-1.31)	(1.10)	(0.61)
Market Concentration (HHI)	1.059*		
	(1.92)		
Industry FE	No	Yes	No

Year FE	No	Yes	No
Industry×Year FE	No	No	Yes
Observations	68,224	60,337	41,370
Pseudo R²	0.771	0.867	0.871

Panel B. First AI Patent

D.V.: First AI Patent	(1)	(2)	(3)	(4)
Value of Non-AI Patents Stock	0.020***	0.047***	0.044***	0.045***
	(32.73)	(10.37)	(10.67)	(10.88)
Value of Software Patents Stock	0.026***	0.101***	0.093***	0.094***
	(9.50)	(9.23)	(8.92)	(8.60)
R&D Intensity	0.132***	0.231***	0.137**	0.127*
	(10.02)	(3.77)	(2.27)	(2.03)
Firm Size	0.003***	0.002*	0.005***	0.005***
	(4.43)	(1.74)	(3.40)	(3.24)
Sales Growth	-0.011***	-0.008***	-0.006**	-0.008**
	(-3.75)	(-2.91)	(-2.38)	(-2.72)
Leverage	-0.040***	-0.013*	-0.007	-0.006
	(-8.99)	(-1.91)	(-1.46)	(-1.23)
External Finance	-0.017***	-0.009***	-0.009***	-0.009***
	(-3.38)	(-3.16)	(-3.58)	(-3.53)
Capital Intensity	-0.060***	-0.033	-0.006	-0.009
	(-3.79)	(-1.38)	(-0.23)	(-0.32)
Age	0.001***	0.001***	0.001***	0.001***
	(14.30)	(4.70)	(4.33)	(4.11)
Market Share	-0.044***	-0.043**	-0.040*	-0.048*
	(-5.16)	(-2.14)	(-1.91)	(-1.77)
Market Concentration (HHI)	0.017***	0.017		
	(3.01)	(1.17)		
Industry FE	No	No	Yes	No
Year FE	No	No	Yes	No
Industry×Year FE	No	No	No	Yes
Observations	59,377	59,377	59,377	59,377
Adjusted R²	0.141	0.108	0.150	0.127

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, CPC×Year, and Firm×Year fixed effects are included as specified in each column. Standard errors are clustered by the patent grant year-firm, and t-statistics are reported in parentheses. All variables are winsorized at the top and bottom 1% of the cross-sectional distribution and defined as outlined in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

D.V.: Patent Value	(1)	(2)	(3)	(4)
AI Patent	0.137***	0.196***	0.066*	0.004**
	(2.71)	(2.87)	(1.94)	(2.14)
Firm Size	0.274***	0.214***	0.268***	
	(5.79)	(3.34)	(6.04)	
Return Volatility	-0.046	-0.188*	-0.053	
	(-0.42)	(-1.83)	(-0.51)	
R&D Intensity (t)	1.072	1.027	0.894	
	(1.56)	(1.05)	(1.35)	
R&D intensity (t-1)	0.112	-0.952	0.056	
	(0.20)	(-0.97)	(0.10)	
R&D intensity (t-2)	1.134	0.296	1.121	
	(1.12)	(0.24)	(1.17)	
Industry×Year FE	Yes	No	Yes	No
CPC×Year FE	No	Yes	Yes	No
Firm×Year FE	No	No	No	Yes
Observations	1,582,696	1,582,691	1,582,691	1,582,696
Pseudo R^2	0.509	0.265	0.523	0.818

Table 5. 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% 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 t-statistics are reported in parentheses. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, 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 6. 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%, 5%, and 1%, respectively.

Panel A. Forward Citations

D.V.: Forward Citations	(1)	(2)	(3)	(4)
AI Patents	0.348***	0.256***	0.224***	0.296***
	(8.86)	(7.39)	(8.81)	(9.30)
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	No
CPC×Year FE	No	Yes	Yes	No
Firm×Year FE	No	No	No	Yes
Observations	1,580,991	1,581,337	1,579,581	1,573,576
Pseudo R^2	0.344	0.340	0.370	0.431

Panel B. CPC-Group Citations

D.V.: CPC-Group Citations	(1)	(2)	(3)	(4)
AI Patent	0.116***	0.140***	0.278***	0.218***
	(3.84)	(3.42)	(5.00)	(4.98)
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	No
CPC×Year FE	Yes	Yes	No	No
Firm×Year FE	No	No	No	Yes
Observations	1,582,691	1,576,489	1,578,484	1,558,691
Pseudo R^2	0.309	0.276	0.263	0.359

Table 7. AI Innovation and Accounting Performance: ROS and Gross Margins

This table examines the effects of AI innovation on Return on Sales (ROS) and Gross Margins 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 independent variables include the market value-weighted cumulative sum of AI patents and all granted patents stock, 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. 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. ROS

D.V.: ROS	(1) Forward 1 year	(2) Forward 2 years	(3) Forward 3 years
Value of AI Patents Stock	0.003**	0.003**	0.001
	(2.21)	(2.28)	(1.27)
Value of Patents Stock	0.001	0.000	-0.000
	(0.93)	(0.05)	(-0.15)
R&D Intensity	-0.081	-0.033	-0.015
	(-1.54)	(-0.59)	(-0.29)
Capital Intensity	0.075**	-0.008	-0.014
	(2.48)	(-0.29)	(-0.32)
Intangible Assets Intensity	-0.044***	-0.034***	-0.030***
	(-4.56)	(-3.66)	(-3.82)
Firm Size	-0.009***	-0.022***	-0.026***
	(-2.92)	(-5.46)	(-6.73)
Book-to-Market Ratio	-0.052***	-0.026***	-0.012**
	(-6.27)	(-4.52)	(-2.70)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	49,868	49,613	49,836
Adjusted R^2	0.517	0.515	0.511

Panel B. Gross Margins

D.V.: Gross Margins	(1) Forward 1 year	(2) Forward 2 years	(3) Forward 3 years
Value of AI Patents Stock	0.002**	0.002**	0.002*
	(2.10)	(2.40)	(1.98)
Value of Patents Stock	0.001	-0.000	-0.001
	(0.67)	(-0.40)	(-0.56)
R&D Intensity	0.140***	0.081*	0.061**
	(2.94)	(2.00)	(2.53)
Capital Intensity	0.061**	0.029	0.037
	(2.83)	(1.31)	(1.30)
Intangible Assets Intensity	0.021***	0.017***	0.011*
	(3.24)	(3.02)	(2.00)
Firm Size	-0.014***	-0.018***	-0.019***
	(-5.26)	(-5.45)	(-6.35)
Book-to-Market Ratio	-0.023***	-0.012***	-0.007**
	(-6.14)	(-4.17)	(-2.48)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	49,114	48,865	49,083
Adjusted R^2	0.854	0.857	0.858

Table 8. AI Innovation and Accounting Performance: Asset Turnover and Employee-to-Sales

This table examines the effects of AI innovation on Asset Turnover and Employee-to-Sales 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 independent variables include the market value-weighted cumulative sum of AI patents and all granted patents stock, 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. 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) Forward 1 year	(2) Forward 2 years	(3) Forward 3 years
Value of AI Patents Stock	0.001	0.002	0.002
	(0.28)	(0.56)	(0.64)
Value of Patents Stock	-0.006**	-0.005*	-0.004
	(-2.45)	(-2.07)	(-1.53)
R&D Intensity	0.033	0.114	0.160**
	(0.48)	(1.55)	(2.54)
Capital Intensity	0.068	-0.139**	-0.195***
	(1.16)	(-2.77)	(-4.21)
Intangible Assets Intensity	-0.357***	-0.275***	-0.207***
	(-15.24)	(-12.60)	(-8.69)
Firm Size	0.040***	0.001	-0.010
	(3.21)	(0.04)	(-0.92)
Book-to-Market Ratio	-0.066***	-0.021**	0.004
	(-5.03)	(-2.68)	(0.93)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	49,868	49,613	49,836
Adjusted R^2	0.898	0.896	0.894

Panel B. Employee-to-sales

D.V.: Employee-to-sales	(1) Forward 1 year	(2) Forward 2 years	(3) Forward 3 years
Value of AI Patents Stock	0.044***	0.040**	0.038**
	(3.21)	(2.59)	(2.48)
Value of Patents Stock	0.025*	0.018	0.015
	(1.76)	(1.35)	(1.15)
R&D Intensity	0.307	-0.198	-0.425
	(0.40)	(-0.25)	(-0.55)
Capital Intensity	0.980***	0.628*	0.425
	(2.98)	(1.90)	(1.43)
Intangible Assets Intensity	-0.117	-0.058	-0.111
	(-1.17)	(-0.66)	(-1.21)
Firm Size	-0.481***	-0.256***	-0.171**
	(-6.49)	(-3.80)	(-2.67)
Book-to-Market Ratio	0.146***	0.076	0.019
	(3.02)	(1.35)	(0.41)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	48,647	48,385	48,614
Adjusted R^2	0.908	0.911	0.913

Table 9. AI Innovation and Market Share

This table examines the effects of AI innovation on Market Share over the three years following patent grants. The market share 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 market value-weighted cumulative sum of AI patents and all granted patents stock, 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. 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.

D.V.: Market Share	(1) Forward 1 year	(2) Forward 2 years	(3) Forward 3 years
Value of AI Patents Stock	0.004**	0.003*	0.003**
	(2.65)	(2.04)	(2.27)
Value of Patents Stock	0.002	0.002	0.002
	(1.50)	(1.68)	(1.37)
R&D Intensity	-0.029***	-0.026***	-0.019**
	(-3.00)	(-3.00)	(-2.32)
Capital Intensity	-0.013	-0.016	-0.015
	(-0.76)	(-0.96)	(-0.97)
Intangible Assets Intensity	0.007	0.005	0.007
	(1.43)	(1.13)	(1.41)
Firm Size	0.018***	0.015***	0.012***
	(6.11)	(5.67)	(5.78)
Book-to-Market Ratio	-0.000	-0.001	-0.001
	(-0.12)	(-0.59)	(-0.85)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	49,868	49,613	49,836
Adjusted R^2	0.856	0.858	0.858

Table 10. 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. Panel A evaluates the impact across all industries, Panel B focuses on the top 25% most concentrated industries, and Panel C analyzes the bottom 75% least 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 market value-weighted cumulative sum of AI patents and all granted patents stock, 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 top and bottom 1% of the cross-sectional distribution and defined in Appendix A. Coefficients marked with *, **, and *** are significant at 10%, 5%, and 1%, respectively.

Panel A. All industries

D.V.: HHI	(1) Forward 1 year	(2) Forward 2 years	(3) Forward 3 years
Value of AI Patents Stock	0.001	-0.001	-0.002
	(0.81)	(-0.34)	(-1.03)
Value of Patents Stock	0.001	0.002	0.002
	(0.55)	(0.72)	(0.89)
R&D Intensity	-0.253	-0.123	-0.064
	(-0.56)	(-0.27)	(-0.14)
Capital Intensity	-0.280*	-0.299*	-0.281*
	(-1.80)	(-2.04)	(-1.84)
Intangible Assets Intensity	0.002	-0.003	-0.020
	(0.05)	(-0.05)	(-0.45)
Firm Size	-0.012*	-0.008	-0.007
	(-1.78)	(-1.25)	(-1.04)
Book-to-Market Ratio	0.014	0.008	0.004
	(0.93)	(0.68)	(0.29)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	4,746	4,738	4,741
Adjusted R^2	0.817	0.820	0.822

Panel B. Top 25% Concentrated Industries

D.V.: HHI	(1) Forward 1 year	(2) Forward 2 years	(3) Forward 3 years
Value of AI Patents Stock	-0.004	-0.010*	-0.015**
	(-0.85)	(-1.79)	(-2.64)
Value of Patents Stock	0.003	0.004	0.005
	(0.59)	(0.71)	(0.98)
R&D Intensity	1.112	1.512*	1.732**
	(1.63)	(1.97)	(2.21)
Capital Intensity	-0.038	0.019	0.077
	(-0.30)	(0.12)	(0.40)
Intangible Assets Intensity	0.055	0.023	0.005
	(0.86)	(0.29)	(0.07)
Firm Size	-0.005	0.003	0.002
	(-0.62)	(0.33)	(0.18)
Book-to-Market Ratio	0.001	0.011	0.004
	(0.07)	(0.52)	(0.15)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1,073	1,067	1,069
Adjusted R^2	0.626	0.643	0.667

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

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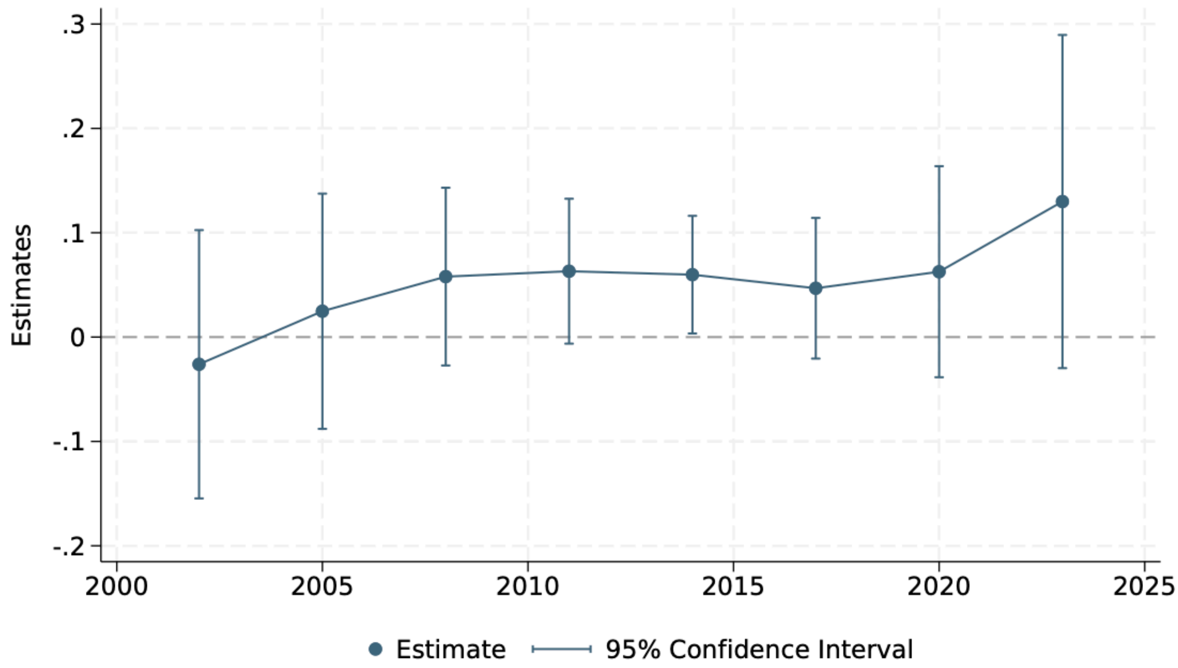
Figure IA1. AI Patents Value Premium by Time Periods

This figure includes two panels presenting the estimated β_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.

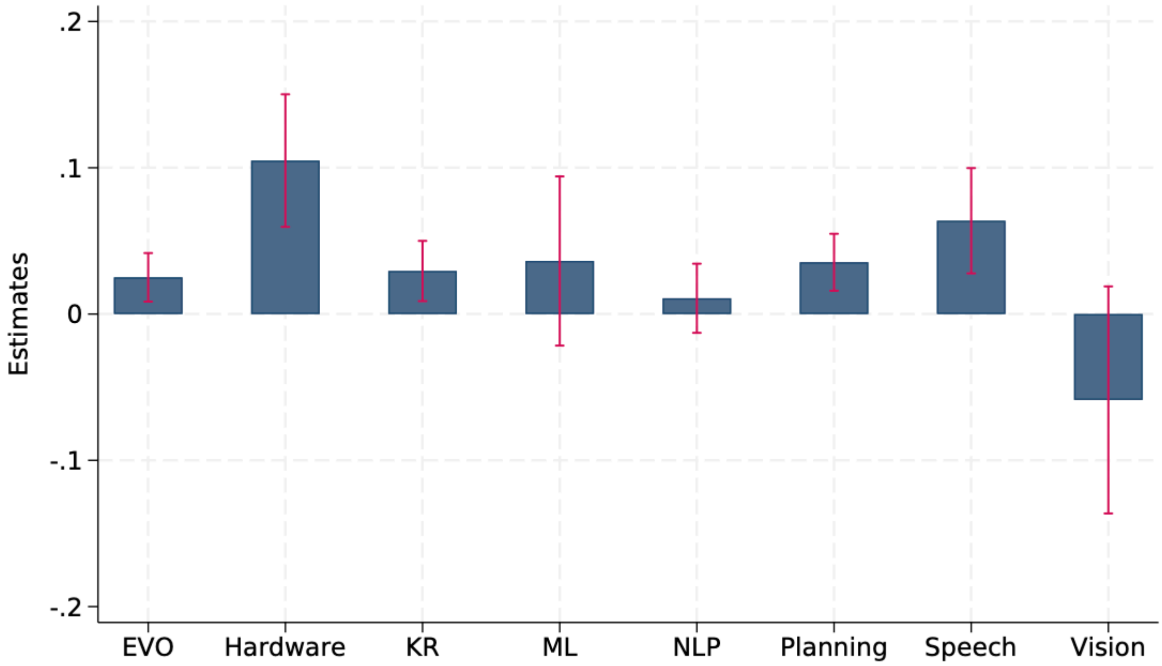
Panel A: Estimated values with CPC patent classification-year fixed effects.



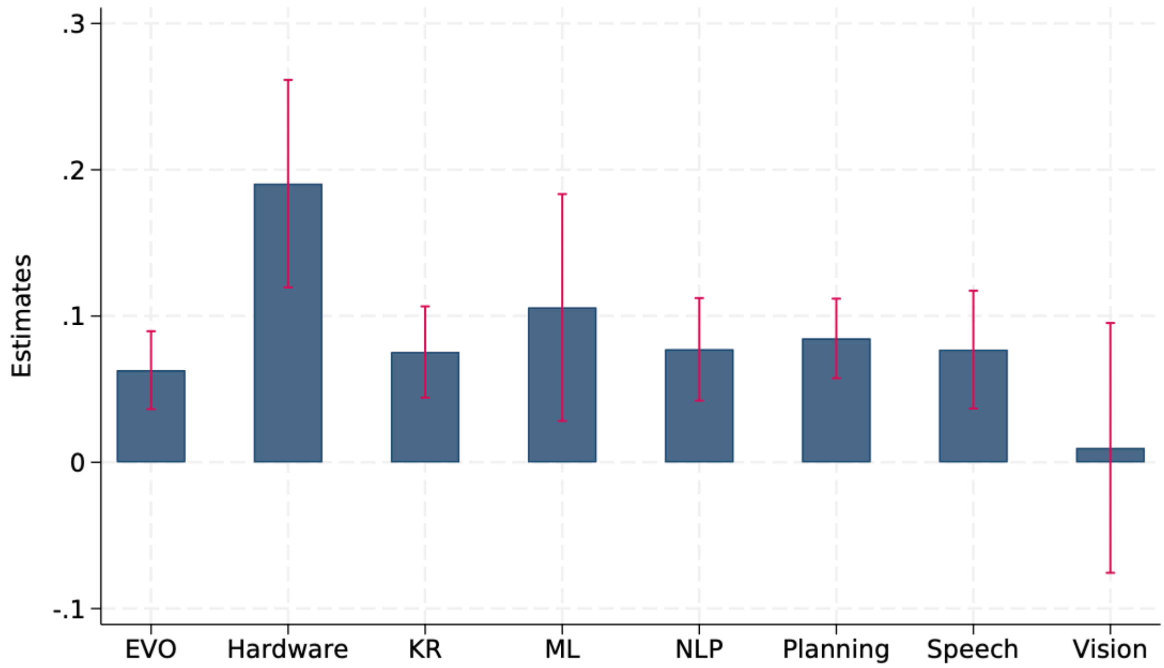
Panel B: Estimate values with CPC patent classification-year and SIC-year fixed effects.

Figure IA2. AI Patents Value Premium by AI Technology Components

This figure includes two panels presenting the estimated β_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. Prior Patenting Activity and AI Patent Value

This table examines the market value premium of AI patents using a Poisson regression model. The analysis is conducted on two subsamples of firms, categorized based on their prior patenting activity over the last five years. Panel A divides firms into two groups: those in the top 25% of total patent stock (Column 1) and those in the bottom 75% of total patent stock (Column 2). Panel B similarly divides firms but based on their AI patent stock, with the top 25% of firms in Column 1 and the bottom 75% in Column 2. The dependent variable is the market value of patents, and the independent variable of interest is whether a patent is classified as AI-related. All specifications include firm-year fixed effects. Standard errors are clustered at the firm-year level, and z-statistics are reported in parentheses. Coefficients marked with *, **, and *** are statistically significant at the 10%, 5%, and 1% levels, respectively.

Panel A. All Patent

D.V.: Patent Value	(1)	(2)
AI Patent	0.005*	0.003
	(1.82)	(1.56)
Firm×Year FE	Yes	Yes
Observations	415,465	1,167,037
Pseudo R^2	0.902	0.794

Panel B. AI Patents

D.V.: Patent Value	(1)	(2)
AI Patent	0.005***	0.003
	(2.48e+09)	(1.01)
Firm×Year FE	Yes	Yes
Observations	416,164	1,166,338
Adjusted R^2	0.869	0.800

Table IA3. 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% of the cross-sectional distribution and defined in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

D.V.: Log Patent Value	(1)	(2)	(3)	(4)
AI Patents	0.365***	0.476***	0.226***	0.003**
	(4.23)	(3.10)	(3.49)	(2.11)
Size	0.094	-0.062	0.100	
	(0.85)	(-0.59)	(0.98)	
Return Volatility	-0.272	-0.534*	-0.276	
	(-0.87)	(-1.89)	(-0.99)	
R&D Intensity (t)	2.298***	1.808	2.058**	
	(3.03)	(1.22)	(2.58)	
R&D Intensity (t-1)	1.419*	0.766	1.363*	
	(1.92)	(0.46)	(1.74)	
R&D Intensity (t-2)	4.304	1.504	4.168*	
	(1.68)	(0.84)	(1.78)	
Industry×Year FE	Yes	No	Yes	No
CPC×Year FE	No	Yes	Yes	No
Firm×Year FE	No	No	No	Yes
Observations	1,582,696	1,582,691	1,582,691	1,582,696
Adjusted R^2	0.416	0.174	0.453	0.968

Table IA4. 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% threshold, while Panel B uses a 50% 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% of the cross-sectional distribution and defined in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

Panel A. 86% Threshold

D.V.: Patent Value	(1)	(2)	(3)	(4)
AI Patents	0.140***	0.197***	0.070**	0.005***
	(2.79)	(2.89)	(2.05)	(2.82)
Size	0.274***	0.214***	0.268***	
	(5.80)	(3.34)	(6.04)	
Return Volatility	-0.046	-0.188*	-0.053	
	(-0.42)	(-1.83)	(-0.51)	
R&D Intensity (t)	1.071	1.027	0.894	
	(1.56)	(1.05)	(1.35)	
R&D Intensity (t-1)	0.112	-0.952	0.056	
	(0.20)	(-0.97)	(0.10)	
R&D Intensity (t-2)	1.133	0.296	1.121	
	(1.12)	(0.24)	(1.17)	
Industry×Year FE	Yes	No	Yes	No
CPC×Year FE	No	Yes	Yes	No
Firm×Year FE	No	No	No	Yes
Observations	1,582,696	1,582,691	1,582,691	1,582,696
Pseudo R^2	0.509	0.265	0.523	0.818

Panel B. 50% Threshold

D.V.: Patent Value	(1)	(2)	(3)	(4)
AI Patents	0.145***	0.183***	0.080**	0.004**
	(3.13)	(2.87)	(2.46)	(1.97)
Size	0.273***	0.214***	0.268***	
	(5.80)	(3.33)	(6.04)	
Return Volatility	-0.046	-0.188*	-0.053	
	(-0.42)	(-1.83)	(-0.51)	
R&D Intensity (t)	1.063	1.024	0.890	
	(1.55)	(1.05)	(1.34)	
R&D Intensity (t-1)	0.108	-0.957	0.055	
	(0.20)	(-0.98)	(0.10)	
R&D Intensity (t-2)	1.130	0.296	1.123	
	(1.12)	(0.24)	(1.17)	
Industry×Year FE	Yes	No	Yes	No
CPC×Year FE	No	Yes	Yes	No
Firm×Year FE	No	No	No	Yes
Observations	1,582,696	1,582,691	1,582,691	1,582,696
Pseudo R^2	0.510	0.265	0.523	0.818