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Abstract

As the latest general-purpose-technology (GPT), we study the value of AI innovations as it diffuses across general and application sectors, using the USPTO's AI patent dataset. Investors value these innovations more than others, as AI patents exhibit a 9% value premium, and 26% higher forward citations compared to non-AI patents from the same patent classification and industry group. This value premium also increases over time, particularly in firms and industries where occupational tasks are more suited for AI. Due to the specialization in AI innovation across general and application sectors, we further find that policies that facilitate knowledge spillovers are key to increasing the value premium in these innovations. Specifically, we show that the value premium of AI innovations in application sectors, increases by 5% after the AIPA patent publication rule, and by 2% after the open sourcing of TensorFlow. Overall, our analysis illustrates the value of AI innovations to investors and highlights the importance of policies that foster knowledge spillovers for AI innovations.

Keywords: Artificial Intelligence, Valuation, General Purpose Technologies, Innovation Disclosure, Open-Source

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

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1 Introduction

Scholars have argued that, throughout economic history, a small set of general-purpose technologies (GPTs), such as steam engines, electricity, computers, and the internet have been at the forefront of driving sustained periods of economic growth (Bresnahan and Trajtenberg, 1995). Thus, when GPTs are first developed, there are substantial economic benefits at stake for society, businesses, and investors. To understand the evolving economic impact of GPTs, in this study, we examine the most recent GPT which is still in development - Artificial Intelligence (AI) technologies, and study the market value of these innovations for the firms that invest in these technologies.[1]

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

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

[1] Our definition of AI technologies includes both the general, enabling AI technology, and the application-specific technologies that use AI.

application sectors, such as retail and wholesale trade, finance, services, and transportation. These striking patterns thus motivate analyses on the value of AI innovations as it diffuses over general and application sectors, and research into the policies that facilitate the knowledge spillovers for these innovations.

We begin our analysis by studying the market assessment of the value of AI patents from 1995 to 2020 that have been identified as such by the US Patent and Trademark Office (USPTO) (Giczy et al, 2022).[23] As prior work has shown robust evidence that patents create value for firms (Hall et al, 2005; Kogan et al, 2017), we examine whether AI patents are *more* valuable compared to non-AI patents (hereafter referred to as the value premium of AI innovations). Our analysis shows that AI patents are roughly 9% more valuable compared to non-AI patents, after controlling for size, research input costs, industry-year and technology-year fixed effects.[4]

Underlying the value premium of AI innovations, are the (1) potential for knowledge spillovers and (2) the wide commercialization opportunities of these technologies. For the first channel, we examine the relationship between AI patents and forward citations. In support of this channel, we show that AI patents exhibit 26% more forward citations compared to non-AI patents, and that investors tend to value the potential of follow-on innovation of AI patents to a greater degree. For the second channel, we examine the

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[2] This data identifies the patents that develop AI technologies, which comprises the enabling AI technologies (formally the GPT in prior theoretical models) as well as the technologies that use AI (or the application technologies of AI). This enables us to examine the core AI technologies in the GPT sector as well as its spillover into application sectors. For our study, we refer to this entire group of AI technologies as "AI patents".

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

[4] We note that the value premium that we measure in our analysis is based on the value of patents measured as of the grant date, which means that the market expectations of capitalized innovation costs are already embedded in prices at this point. Furthermore, to address concerns that markets do not fully capitalize expenditures in intangibles, like R&D, we also control for past expenditures on innovation, as measured by the past 5-year average of R&D intensity, 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.

relationship between AI patents and operating performance. We find that the number of AI patents (equal and value-weighted) is associated with 2- and 3-year ahead higher profit margins, but not with future asset turnover.[5] Taken together, our analysis suggests that AI innovations enable firms to increase future profitability and to spur future innovations.

Over time, we find that the value premium of AI innovations also rises *persistently* across a 20-year period from 2000-2020 (see Figure 3). To examine the drivers of this trend, we examine several factors, and we show that the gradual pricing of the technical benefits of AI likely explains this upward trend in the value premium of AI innovations. Specifically, we find that industries and firms where occupational tasks are more suited for AI technologies (based on Felten et al, 2021), exhibit a 0.5% increase in the value premium of AI innovations per year, after controlling for overall interest and investor uncertainty over AI technologies.

Next, we probe into the specialization of and knowledge spillovers between general (upstream) and application-specific (downstream) AI innovations. Prior research on GPTs, suggests that there are different development needs of the general, enabling technology and the application-specific technology (Bresnahan and Gambardella, 1998), which leads to domain specialization. For general AI innovations, we conjecture that the IT industry would be more specialized in the development of these innovations, as this industry specializes in software development, which facilitates the creation of core algorithms that enable follow-on innovation (i.e. the general, enabling AI patents). Consistent with this view, we find that the general AI patents exhibit a 4% higher market value compared to other AI patents in the IT industry.[6] On the other hand, for application-specific AI innovations, we expect that non-IT

[5] The fact that we find profit margin increases but limited evidence on asset turnover increases should also alleviate concerns that the relationship between AI patents and increases in profitability is due to accounting rules that limit the capitalization of research and development expenditures. As profit margins are scaled by sales, the growing intangibility of the firm due to AI investment likely has a limited impact on this ratio.

[6] General patents are defined as patents that receive forward citations from at least 3 cooperative patent classification (CPC) groups. The CPC is a classification scheme used by the USPTO and the European Patent Office to index patents and to help patent examiners search for similar patents. Prior research on patents has used this scheme to group patents along similar technology classes (e.g. Webb et al, 2018).

industries should specialize in the development of these innovations, as such innovations should benefit from complementary knowledge in non-AI but application-specific technologies. Aligning with this view, we find that application-specific AI patents exhibit a 3% higher market value compared to other AI patents in the non-IT industries.[7] Thus, our evidence suggests that firms in IT (non-IT) industries specialize in developing general (application-specific) AI technologies.

Due to specialization in the development of general and application-specific AI technologies, innovation policies that encourage knowledge spillovers between sectors and firms could play a particularly important role in unlocking the downstream (application-specific) value of AI innovations. To examine this question, our last set of analyses study whether two policy changes that enhanced the disclosure and public use of innovations, also increased the value of AI innovations relative to non-AI innovations in application sectors.

For the first policy change, we examine the 18-month publication rule that came into force after the passage of the American Inventor Protection Act (AIPA) in 2000. This policy mandated the disclosure of filed patent applications within 18-months of the filing date, which (1) increased the speed of patent disclosures and (2) unveiled details of patent applications that did not receive patent protections (Kim and Valentine, 2021; Hegde et al, 2023). In a difference-in-difference (DiD) framework, we find that the passage of this act is associated with a 5% increase in the value premium of AI innovation for application sectors, and is also preceded by insignificant pre-trends in the years before its passage.

For the second policy change, we examine Google's unexpected decision to open-source TensorFlow in 2015, which played an important role in the development of AI innovation

[7] Application-specific patents are defined as patents that receive forward citations from only 1 CPC group.

(Rock 2022).[8] Consistent with the view that open-sourcing TensorFlow increased knowledge spillovers and the use of AI technologies, our DiD estimates suggest that TensorFlow increased the value of AI patents relative to non-AI patents by 2% in application sectors, and is also preceded by stable pre-trends in the years before the introduction of TensorFlow.

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. Moreover, we find some evidence that the value of AI innovations is anchored on the expected benefits of these technologies to firms, rather than on fluctuations in the overall interest in these technologies.

Second, we also contribute to studies that examine knowledge spillovers in innovation. Recent research has identified knowledge spillovers as an important driver of of inventive activity and investments (Hegde and Luo, 2018; Byun et al, 2020; Matray, 2021; Bustamante and Fresard, 2021; Grieser et al, 2022; Dyer et al, 2023). We contribute to this body of work by studying a group of technologies that exhibit particularly large knowledge spillovers, due to the *economic-wide* diffusion of innovation in GPTs. Specifically, we find that AI innovations exhibit substantially more forward citations compared to other innovations, and that the potential of follow-on innovation in these innovations are valued more.

[8] Rock (2022) argues that Google's decision to open source TensorFlow was an unexpected event that surprised many in the software industry, and shows that this event had a large impact on market valuation for AI firms.

Our study also has important implications for investors, managers and policy-makers. For investors and managers, our findings show that AI innovations are particularly valuable for firms, but also that the development of certain types of AI technologies are more valuable in certain sectors, due to industry-specific domain expertise. In addition, from a policy-making perspective, we show that innovation policies within *and* outside of the patent system, such as open sourcing TensorFlow, substantially increase the value premium of AI technologies in the application sectors. Notably, the latter finding reinforces the idea that certain key software in AI's development can be viewed as a public good, where open-access to these software can lead to large economic gains for many firms (Nagle, 2018; Hoffman et al, 2024).

2 Conceptual Framework

2.1 AI as the Latest 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) widely used, (2) capable of ongoing technical improvements and (3) enabling innovation in application sectors. These features are particularly important, as they lead to two economic effects that distinguish GPTs relative to other technologies. First, GPTs exhibit knowledge spillovers and diffusion in innovation across sectors. Second, these technologies are also widely applied across multiple sectors of the economy, which could drive operational gains in a broad set of firms.

Recent work studying the economic impact of AI has argued that the complementary group of AI-related technologies - analytics, big data, and machine learning are GPTs

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

In this study, we investigate investor assessments of the value of AI innovations, defined as the innovations in the group of technologies that includes the general, enabling AI technology and the application-specific technologies that use AI. To guide our analysis, we rely on the theory of GPTs to develop hypotheses on the market value of AI innovations, in the subsections below.

2.2 Investor Assessment of the Market Value of AI Innovation

Our core 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 also 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. Hence, 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:

H1: The value of AI innovations is no different from the value of non-AI innovations.

2.2.1 The Value Premium of AI Innovations Over Time

The long development lags of AI innovations, leads to further questions on the pricing of AI innovations over time. One view is that the value premium of AI innovations should exhibit a steady increase, as the technological capabilities of the technology unfolds. Prior research shows that the future benefits of the GPTs tend to be unknown until multiple years of lags (Bresnahan et al, 2002; Brynjolfsson et al, 2019), which creates uncertainty over the value of

AI innovations as it emerges. Consequently, investors may choose to price in the economic benefits of AI innovations, only when the subsequent technical improvements are developed.

On the other hand, others have also argued that the value of GPTs could also vary by the hype in the technologies over time. Studies on the previous wave of GPTs, the internet technologies during the 1990s, found some evidence that market expectations for firms which invested in these technologies were too high (Healy and Palepu, 2003; O'Brien and Tian, 2006), and others showed salient examples of mispricing of technology stocks during this period (Cooper et al, 2001; Lamont and Thaler, 2003). From a rational expectations viewpoint, Pastor and Veronesi (2006) further show that the changes in the uncertainty of growth rates of new technologies also explains the jump in the value of internet firms during the late 1990s, which provides another reason that could explain changes in the value premium of AI innovations over time. Collectively, both of these viewpoints predict a hump-like pattern in the value premium of AI innovations, that is - there is an initial run-up in the price of these innovations, followed by a decline in prices when interest wanes, or when discount rates rise (Pastor and Veronesi, 2009).

Hence, the overall discussion suggests that it is ex-ante unclear if we would observe a gradual increase or a hump-like pattern in the value premium of AI innovations. Consequently, we examine the following the hypothesis:

H1a: The value premium of AI innovations increases gradually over time.

2.3 Market Value of General and Application-Specific AI Innovations

A potentially distinguishing feature of AI, compared to other technologies, is the specialization in the upstream development of enabling technologies, and the downstream development of the technologies that revolve around AI. Specifically, we expect that the general, enabling AI technologies are first developed in a core sector (the general sector), and the applications of AI technologies are subsequently developed in other sectors (the application sectors).

What drives this specialization in the invention of general, enabling AI technologies and application-specific AI technologies, is the economies of scale in developing general technologies (Bresnahan and Gambardella, 1998). We argue that for AI technologies, IT firms will exhibit economies of scale in the development of general AI technologies, as IT firms focus on software development, an expertise that is critical in the development of core algorithms and hardware that power AI technologies. Thus, we expect that:

H2a: General AI innovations are more valuable in the IT industry.

For AI innovations that are related to the use of AI in application sectors, we expect a different type of specialization that arises from the localization needs of the technology at the sector level (Bresnahan and Gambardella, 1998). Specifically, prior work suggests that the development of follow-on, application-specific innovations demands fine-tuning for distinct applications of GPTs (Conti et al, 2019). Understanding the nuances of fine-tuning technologies for specific applications would require existing knowledge in the current technologies and customer demands of a particular industry, which is more likely found in non-IT firms. Thus, we further expect the following hypothesis:

H2b: Application-specific AI innovations are more valuable in the Non-IT industries.

2.3.1 Policies on Innovation Knowledge Spillovers and the Value of AI Innovations

Due to the specialization in the development of general and application-specific AI technologies, knowledge spillovers across sectors and firms, likely play a critical and particularly pronounced role in facilitating the development of AI technologies (compared to other types of technologies) in downstream, application sectors.

One way of encouraging knowledge spillovers is through policies that facilitate the disclosure and public use of prior innovations. Within the patenting system, disclosure rule changes through American Inventor Protection Act (AIPA) in 2000, have increased the amount of information that is provided to other inventors when inventions are filed for patent protection. Specifically, under the AIPA rules, patents that are filed with the USPTO have to be published within 18 months from the filing date. Thus, post-AIPA, the details of filed patent applications have to be publicly disclosed earlier (Kim and Valentine, 2021; Hegde et al, 2023) and even when patent protections are not granted.

We expect that this rule change will have a more pronounced impact on AI innovation in the application sectors due to the specialization in the development of general and application-specific AI innovations. Specifically, these specialization forces increase the need for knowledge spillovers from the general to application sectors, to facilitate technological developments in application-specific AI. Consequently, we expect that:

H3a: The passage of AIPA increases the value premium of AI innovations in application sectors.

Outside of the patenting system, recent movements towards open-sourcing key software (Nagle, 2018) are additional innovation policies specific to the AI setting that can facilitate knowledge spillovers in a substantial way. In particular, Google's decision to open-source a critical software in AI development - TensorFlow - stands as a landmark event that arguably increased the spillover of AI knowledge substantially to downstream (application) sector firms. For AI developers, TensorFlow is an important enabling innovation, as it is a widely-used platform of software tools that enables developers to develop and implement machine-learning (ML) and deep-learning algorithms. Consistent with this notion, prior work has shown that open-sourcing TensorFlow had an economically large impact on the value of firms that heavily adopted AI (Rock, 2022).

For AI innovations, we would expect similar effects on the value of these innovations, because the open sourcing of TensorFlow, reduces the barriers to learning and training ML models, which in turn, facilitates the development of downstream AI applications. Specifically, in application sectors where prior knowledge in ML algorithm development is comparatively low, the open-source access to TensorFlow facilitates the rapid spillover of AI knowledge to these sectors and increases the value premium of AI innovation. Hence, we would expect the following hypothesis:

H3b: Open-sourcing TensorFlow increases the value premium of AI innovations in application sectors.

3 Data and Research Design

3.1 Data Sources and Sample Selection

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 2020 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 1,857,451 patents that have information on technology class and can be linked to a public firm assignee, involving 4,999 public firms with grant years spanning from 1995 to 2020.[9]

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 with complete financial information for the subsequent year, we compile a comprehensive dataset comprising 93,464 firm-year observations.

Additionally, to reduce the impact of outliers, in all regression analyses, we winsorize continuous variables at the top and bottom 1% of the cross-sectional distribution.

3.2 Research Design

To empirically examine the value implications of AI innovation, we estimate the following regression model in a patent-year panel:

$$Log\ Patent\ Value_i = \alpha + \beta_1 AI\ Patents_i + \beta_2 Log\ Firm\ Size_i + \beta_3 RetVol_i + \beta_4 Log\ Citations_i + \beta_5\ R\&D_i + CPC \times Year\ FE + Industry \times Year\ FE + \varepsilon_i. \quad (1)$$

[9] We chose 1995 as the starting point as the share of AI patents compared to all patents was low (less than 5%).

The dependent variable ($Log\ Patent\ Value$) is defined as the natural logarithm of patent value, adjusted to 1982 (million) dollars using the consumer price index (CPI).[10] We log transform patent value to account for its skewed distribution (Lerner and Seru, 2022). $AI\ Patent$ is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, identified in the AIPD. The key coefficient of interest in Equation (1) 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.[11]

Equation (1) 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 ($Industry \times Year\ FE$).[12] 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 the log-transformed market capitalization of patent-holding firms on the day before the patent issuance date ($Log\ Firm\ Size$), the return volatility ($RetVol$), and the quality of innovation as proxied by the log-transformed number of citations received by the end of 2022 ($Log\ Citations$).[13] Additionally, we control for the research input costs, with the past 5-year average R&D intensity ($R\&D$). Following Kogan et al. (2017), we cluster the standard errors at the grant year level to avoid biased estimates.

[10] 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 past 5-year average R&D intensity.
[11] 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.
[12] The CPC is the latest patent classification scheme that is jointly used by the USPTO and the EPO.
[13] The inclusion of CPC x Year FE addresses the truncation biases in patent citations (Lerner and Seru, 2022).

4 Results

4.1 Descriptive Analysis

4.1.1 The Evolution of AI Patents

We begin our analysis by examining the development of AI innovations from 1995 to 2020, as depicted in Figure 1. At the beginning of our sample period, AI patents granted to public firms were relatively scarce, comprising only about 1700 per year, which represented a modest 5% of the total patents issued. In the following years, we observe a consistent annual growth at an average rate of 10%, culminating in the issuance of over 26,000 AI patents in the year 2020. Notably, AI patents have become increasingly prominent, representing about 27% of the total patents granted to public firms.[14] This trend underscores the rising significance and proliferation of AI technology in innovation firms.

Next, Table 1 examines the industry distribution of AI patents categorized by 2-digit SIC major groups. Unsurprisingly, the IT sector (SIC Code 737), which is part of SIC code 73 (*Business Services*), accounts for 42% of AI patents (130,645 out of 308,216 AI patents). This is followed by the sectors of *Industrial and Commercial Machinery and Computer Equipment* (SIC code 35) and *Electronic and Other Electrical Equipment and Components, excluding Computer Equipment* (SIC code 36).[15]

Next, we study the transitions and spillovers of AI technologies. 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

[14] In Figure IA1, 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.

[15] To be more precise, the IT industry is more accurately defined by the 3-digit SIC code 737, as used later in the regression analysis. For simplicity, the results in Table 1 are presented based on the 2-digit SIC code. This simplification does not pose a significant issue, as an overwhelming majority, 130,332 patents (99.76%), of the 130,645 patents in sector 73 originate from code 737.

technologies in various non-IT sectors (Bresnahan, 2010). As depicted in Figure 2, the development of AI originated in the IT sector and has since permeated into multiple major industries, including retail and wholesale trade, finance, services, and transportation.

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, 17.1% of patents granted to public firms are identified as AI patents, with 13.7% emanating from the IT industry. The average patent holds a value of $11.45 million and receives 12.38 forward citations, while the average AI patent holds a value of $14.20 million and receives 15.14 forward citations. At the firm-year level, an average firm is granted 1.5 AI patents and 12.6 patents in each year.[16]

4.2 Are AI Innovations More Valuable?

4.2.1 Baseline Results

Our next set of analyses focuses on the market values of AI patents. Building on prior research demonstrating that patents generally add value to firms (Kogan et al, 2017; Hall et al, 2005), we investigate whether AI patents hold greater market values compared to non-AI patents ($H1$) by estimating Equation (1) and reporting results in Table 3. In Column (1), we include grant year ($Year\ FE$) interacted with subsection-level CPC technology classes fixed effects ($CPC\ FE$) and grant year ($Year\ FE$) interacted 3-digit SIC industry groups fixed effects ($Industry\ FE$), as outlined in Section 3.2. Our analysis in this column shows that AI patents are, on average, approximately 11% more valuable than non-AI patents (coef. = 0.112, t-stat = 20.71).

[16] In determinant analyses reported in Table IA1 of the IA, we also find the following factors determine the patenting of AI technologies relative to non-AI technologies. Size, sales growth, external financing, past AI patenting activity, R&D intensity and IT industry membership are positively related to AI patenting activity. Leverage ratio and past non-AI patenting activity are negatively related to AI patenting activity.

As Hall et al (2005) show that part of the market value of patents is driven by the academic quality of the patent (i.e. the forward citations), we control for forward citations in Column (2). With the inclusion of this control, we find that AI patents are, on average, 9.1% more valuable than non-AI patents. To place our results in context, the 9.1% effect in Column (2), translates to a value premium of 1 million in 1982 dollars (estimated as 9.1% of 11.45 million) or 3.12 million in today's dollars per AI patent compared to non-AI patent within the same technology class and industry group and granted in the same year.[17]

Furthermore, to address the potential confounding effect that arises from differences in R&D inputs and expenditures, we add R&D intensity, averaged over the past 5-years, as a control variable in Column (3). Notably, we find that the inclusion of this control has a minimal effect on the economic magnitude of the value premium of AI innovations, which suggests that the differences in R&D expenditures plays a minimal role in explaining the value premium of AI innovations.[18]

4.2.2 Sources of the Value Premium of AI Innovations

To delve into the sources of the value premium in AI innovation, we hypothesize from the GPT framework. This framework predicts that the key drivers of the value premium are (1) the knowledge spillovers that increase complementary innovation in application sectors (i.e. the knowledge spillover channel) and (2) their wide applicability, potentially leading to substantial commercial value (the commercialization channel).

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[17] 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). With these components, we assess and compare the value premium of each AI component against non-AI patents. The results, presented in Figure IA2 of the IA, indicate that Planning and Control, Hardware, Knowledge Processing, and NLP exhibit an approximately 15% higher value premium relative to non-AI patents. Notably, Computer Vision is the only component among the eight that shows a similar market value compared to non-AI patents.

[18] As further robustness analysis, we examine whether the value premium of AI innovations holds under alternative modeling specification of the dependent variable. We show in Table IA2 and Table IA3 in the IA that our results are qualitatively similar when examined under the Poisson model and the Inverse Hyperbolic Sine model.

We first examine the knowledge spillover channel, by comparing the number of future citations of AI patents with non-AI patents. A plausible explanation for the value premium of AI innovations is their superior quality and notable influence on future innovation. Prior research shows that investors tend to place a premium on higher-quality patents that lead to more future innovation (Hall et al, 2005; Kogan et al, 2017), and thus we conjecture that higher forward citations (or higher quality) could be a reason that explains the higher market values of AI patents. Supporting this hypothesis, Panel A of Table 4 shows that AI patents typically receive 26% more forward citations than non-AI patents (coef. = 0.26, t-stat = 7.35 in Column (2)).

Furthermore, we examine whether investors value the greater potential for follow-on innovation at stake for AI patents to a greater extent than non-AI patents. If investors expect that follow-on innovation is more important to the value of AI patents, then the market value of these patents should be more sensitive to proxies of the potential for follow-on innovation. In Panel B of Table 4 we present this set of analyses, by using forward citations as a proxy for the potential for follow-on innovation (or inherent quality of the patent) following Kogan et al (2017). Consistent with the findings of Kogan et al (2017), we first find a strong and positive association between forward citations and market values, as shown in Columns (1) and (2). More importantly, we show that this positive correlation is more pronounced for AI patents, by 7.5% compared to non-AI patents. This result is consistent with the idea that investors tend to value the potential for follow-on innovation in AI patents more, compared to other types of patents.

Next, we examine whether the commercializability of AI is a driver of the value premium in AI innovations. AI technologies can generate economic benefits to firms for a variety of reasons. For example, the adoption of new AI technology can enhance the quality of products or services, potentially leading to increased pricing power. AI can reduce production costs, contributing to higher profit margins. Additionally, AI technologies can also streamline operational processes, thereby increasing the efficiency with which assets are deployed. Thus, if AI technologies are widely used by firms, we would likely find improvements in operating performance when these technologies are developed.

To examine this hypothesis, we investigate the associations of AI patenting activities and key financial metrics of firms. Specifically, we estimate the following equation:

$$Financial\ Metric_{f,t} = \alpha + \delta_1 Log\ \#\ of\ AI\ Patents_{f,t} + \delta_2 Log\ \#\ of\ All\ Patents_{f,t}$$
$$+ \delta_3 Log\ \#\ of\ Software\ Patents_{f,t} Controls + Firm\ FE + Year\ FE + \varepsilon_{f,t}, \quad (2)$$

Where we estimate the regression for the various financial ratios ($Financial\ Metric_{f,t}$) for firm f and year t. Although our primary emphasis is on the number of AI patents granted in a year ($Log\ \#\ of\ AI\ Patents$), we also incorporate the total number of patents ($Log\ \#\ of\ All\ Patents$) and total number of software patents ($Log\ \#\ of\ Software\ Patents$) granted in a year in our analysis , which acts as a control for overall innovation activities and provides a benchmark for comparison. We include firm and year fixed effects to account for time-invariant omitted variables biases and confounding time-trends.[19] Moreover, as the market value of patents is influenced by uncertainties in technology applications and delays in commercialization, we also examine the speed at which AI patents provide tangible economic benefits to firms with this firm performance analysis. Specifically, to study this question, we implement the regression model in Equation 2 with the financial performance metrics ($Financial\ Metric_{f,t}$) measured in the 1-3 year ahead horizons.

We tabulate the results in Table 5. The number of patents granted in a year is counted either on an equal-weighted basis in Columns (1) to (3) or weighted by the market value of

[19] The sample excludes observations with missing data on assets, net income, market capitalization, and book-to-market value ratio. Additionally, we eliminate observations with an abnormal negative return-to-sales ratio (smaller than -1).

patents in Columns (4) to (6) to emphasize the role of high-quality innovation. To start with, we examine the profitability of firms with *ROS* in Panel A. The analysis in this panel reveals that a 10% increase in the equal-weighted (value-weighted) number of AI patents is associated with a 9% (3%) increase in profit margins two years ahead, and a 5% (3%) increase three years ahead.

Additionally, we further highlight two other interesting observations in this panel. First, across both weighting specifications, AI patents do not exhibit a significant correlation with profit margins in the one-year ahead, suggesting a slight delay in the application or commercialization of the technology. Second, we note that the total number of patents does not predict future profitability, reinforcing our argument that AI patents are more readily convertible into tangible economic profits and, as a result, are highly valued. Collectively, these findings imply that AI patents facilitate a relatively fast development of new products and services, or reductions in production costs, leading to higher profit margins in the 2-3 years after the patenting of AI technologies.

In Panel B, we examine the relationship between the equal-weighted and value-weighted number of AI patents and future asset turnover. In contrast, to the profit margin results, we find limited evidence of an association between the patenting of AI technologies and future asset turnover. This results suggests that AI patents exhibit positive profitability effects but have a limited impact on the efficiency in the deployment of assets

4.3 Time-Series Changes in the Value Premium of AI Innovations

One of the important features of AI is that these technologies exhibit gradual technical improvement over time. These technical improvements, therefore suggest that the value premium of AI innovation should rise as the capabilities of the technology improves. Motivated by this prediction, we examine whether the value premium of AI innovations rises over time (*H1a)*, and we study the reasons that could explain the temporal changes in market values in this subsection.

In Figure 3, we show that the value of AI innovation is rising over time. Specifically, we examine the analysis in Table 3 in five-year buckets, and we document a consistent increase in the value premium of AI patents relative to non-AI patents over time. Specifically, between 1995 and 2000, the market value of AI patents was not significantly different from that of non-AI patents. However, in the subsequent 15 years, the value premium expanded to 10% and became significantly different from 0. Notably, in the latest five-year period from 2016 to 2020 in our sample, the value premium peaked at 13.5%. This overall trend reflects a steady increase in the market's recognition of the value of AI, and addresses *H1a* by showing that the value premium of AI innovations exhibits a steady increasing trend.

The rising value premium of AI innovation over time motivates natural questions on the reasons that explain this trend. While improvements in the technical capabilities of AI over time could explain the increasing value premium of AI innovation, other factors such as investor sentiment or the uncertainty over the growth potential of the technology (Pastor and Veronesi, 2006) could also explain temporal changes in this value premium. Thus, in the following analysis, we examine whether the time-series variation in these factors explain the value of AI innovations over time.

Table 6, presents this analysis. In Column (1) we interact the indicator for AI patents with a time-trend variable (i.e. the number of years since the start of the sample in 1995), to estimate the magnitude of the time-trend. Our estimates show that AI innovations did not exhibit a significant value premium in the initial years of the sample, but over time, the value premium of AI innovation increases by 0.4% per year.

If the value premium of AI innovation increases due to the technical improvements of the technology over time, we would expect that the upward trend in the value premium should be more pronounced in firms and industries that benefit more from these technologies in recent years. To test this hypothesis, we aggregate the 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 industry- and firm-level, and study whether the increase in the value premium of AI innovation is concentrated in these industries and firms.[20] In Column (2), we analyze the time-trend of the value premium of AI innovations in industries that exhibit high AI suitability, and we find that this premium rises by 0.5% per year. In Column (4), we further examine whether the time-trend of the value premium in AI innovation is higher for firms that exhibit high AI suitability, and we also find that this value premium rises in these firms by 0.6% per year.[21]

As the changes in the value premium of AI innovations could be driven by fluctuations in overall interest and investor uncertainty over these technologies, in Columns (3) and (5), we control for these factors in the regression model. Specifically, we include an interaction between the indicator for AI patents and the google trend score of AI technologies for a given year, and the standard deviation of the value of AI patents in the same technology group for a given year. With these controls for the interest and uncertainty over AI, our analysis in these columns shows that the time-trend in the value premium in AI innovations continues to be concentrated in the industries and firms that exhibit high AI suitability. Moreover, we also find that our proxies for overall interest in AI do not exhibit a significant relationship with the value of AI innovations over time, while the proxy for investor uncertainty over AI exhibits a positive relationship with the value premium of AI innovations (consistent with Pastor and Veronesi, 2006).

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[20] We aggregate the occupational-level AI suitability scores at the industry score using the BLS employment data using the data provided by Felten et al (2021). For the aggregation at the firm-level, we measure the occupation of workers in firms in 2020, using data for a sub-sample of firms provided by *RevelioLabs*.

[21] In untabulated analysis, we examine the time-trend in the value premium of AI innovations for firms that exhibit a high exposure to AI technologies with the exposure measured on a salary-weighted basis. Our results are qualitatively similar with this alternative specification.

4.4 Value Premiums of General and Application-Specific AI Innovations

As discussed in Section 2.3, the innovations in AI technologies can be chiefly categorized into two groups, namely the (1) general, enabling and (2) application-specific AI innovations. Thus, in this subsection, we analyze the differences in the patent market values across these types of AI innovations.

4.4.1 General vs. Application-Specific Patents

To examine the differences in the market values of general and application-specific AI innovations, we categorize two types of patents, namely, the general patents that are cited by more than 3 CPC groups and the application-specific patents that are cited by only 1 CPC group. Due to the different specialization needs that are involved in the development of the both types of innovations, we expect significant cross-sectional variation in the value of these patents across different industries (*H2a and H2b*).

We first focus on the general AI patents and test the prediction that the IT industry specializes in the development of these patents (*H2a*), by studying the values of general AI patents across the IT and non-IT industries. In Columns (1) and (2) of Table 7, we compare the value of general AI patents across these sectors. Consistent with our predictions, we find that the value of general AI patents is indeed higher in the IT sector. Our estimates show a 4% value premium for general AI patents compared to other general patents in the IT industry (coef. = 0.038, t-stat = 2.39 in Column (1)). Moreover, the comparison of the value premium of general AI patents and general non-AI patents across the IT and non-IT industries show that this value premium is 8% higher in the IT industry (coef. = 0.080, t-stat = 4.13 across Columns (1) and (2)).

Next, we turn to the application-specific AI patents and test the prediction that the non-IT industry specializes in the development of these patents (*H2b*), by studying the values of application-specific AI patents across the IT and non-IT industries. We present these findings in the following two columns of Table 7, and we find results consistent with our predictions. Specifically, we find that application-specific AI patents are 3% more valuable compared to other application-specific non-AI patents in the non-IT industries (coef. = 0.027, t-stat = 2.78 in Column (4)). In addition, we compare the value premiums of application-specific AI patents across the non-IT and IT sectors, and we find that this value premium is also 6% higher in the non-IT sector (coef. = 0.065, t-stat = 3.18 across Columns (4) and (3)).

Overall, these cross-sectional analyses suggest that there is specialization in the development of general and application-specific AI innovations.[22] Specifically, our analysis suggests that the IT sector serves as the general sector for AI innovation, while the non-IT industries function as the application sectors in the context of AI innovation.

4.4.2 AIPA and the Value Premium of AI Innovations in Application Sectors

GPTs such as AI require knowledge spillovers between general and application sectors to facilitate continuous technical change that broadens the use-cases of the GPT and unlocks the growth potential of these technologies. Moreover, as the development of general and application-specific AI technologies tends to be specialized, knowledge spillovers between the upstream (general) sectors and downstream (application) sectors are particularly important, as these spillovers connect innovation across these two different domains of specialization.

Due to these factors, policies that facilitate the disclosure and public use of prior innovations could play a key role in driving knowledge spillovers and the value of AI innovations in downstream applications of AI technologies. Thus, we study how two policy changes on innovation policies increased the value of AI innovations in application sectors.

[22] In the IA, we examine additional cross-sectional analyses based on the historical quality of the AI innovation of the firm, and whether the AI innovation is explorative or exploitative from the firms' perspective. In Table IA4, we find that firms with historically high quality of AI innovations, as measured by the citation counts, tend to exhibit a higher value premium in AI innovations. In Table IA5, we measure explorative (exploitative) patents following Fitzgerald et al (2020) and find that explorative AI innovations for firms exhibit a higher value premium compared to exploitative AI innovations.

The first policy change that we examine is the patent publication rule in the American Inventor Protection Act (AIPA), which was enacted in 2000. This rule change mandated the publication of all filed patent applications by the 18-month of the filing date. Thus, the rule change accelerated the disclosure of patent information before patent protections were granted (Hegde et al, 2023) and also revealed the patent information of patent applications that were not granted patent protections. Prior research showed that this rule change increased knowledge spillovers between inventors (Kim and Valentine, 2021; Hegde et al, 2023), which justify the use of this setting to test the impact of increases in knowledge spillovers and the value premium of AI patents.

To test the question of whether the passage of AIPA increased the value premium of AI patents relative to non-AI patents (*H3a*) we implement a difference-in-difference analysis. For this test, we focus on monthly data in the eight-year period centered on AIPA's passage in November 2000, spanning from November 1997 to May 2005. We exclude November 2000 to May 2001, as the benefits of accelerated disclosure from the patents filed after the enactment of AIPA began to emerge after this 18-month period. We estimate the following regression based on a sub-sample of 327,386 patents in a patent-month panel for application sector (non-IT) firms:

$$Log\ Patent\ Value_i = \alpha + \gamma_1 AI\ Patents_i \times Post\ AIPA_t + \gamma_2 AI\ Patents_i + Controls + CPC \times Month\ FE + Industry \times Month\ FE + \varepsilon_i. \quad (3)$$

The primary variables are defined in the same way as those in Equation (1) and we include the same set of control variables. $Post\ AIPA$ is an indicator variable equal to 1 for periods after the passage of AIPA in November 2000 and 0 otherwise. To account for the more rapidly evolving technological trends within this shorter timeframe, we incorporate a more detailed fixed effect structure, including subsection-level CPC technology classes interacted with grant month fixed effects ($CPC \times Month\ FE$) and 3-digit SIC industry groups interacted with grant month fixed effects ($Industry \times Month\ FE$).

In Table 8, we report the estimates of the DiD regression based on Equation (3). Consistent with *H3a*, we find that the passage of AIPA is associated with a marked increase in the value premium of AI patents relative to non-AI patents for firms in the application sectors. Specifically, Column (1), which includes technology group-month FE and industry-month FE, shows that the post-AIPA AI patents in these firms are 5.2% more valuable than AI patents granted prior to AIPA. Column (2), which includes additional controls for the logarithm of citations and R&D intensity, also shows that AI patents that are granted after AIPA are 5.5% more valuable compared to non-AI patents in non-IT firms. Overall, these findings are in line with our expectation that the enactment of AIPA benefits the downstream development of AI technologies in application sectors (or non-IT industries).

The causal interpretation of a DiD model hinges on the validity of the parallel trends assumption. To assess parallel trends, we estimate a dynamic model by including a set of dummy variables that indicate each year before and after the passage of AIPA and use the last 12 months before AIPA as the benchmark year (Nov 1999 to Oct 2000):

$$Log\ Patent\ Value_i = \alpha + \sum_{k=-2,-1}^{1,2,3} \gamma^k AI\ Patents_i \times 1_{Year_k=1} + \gamma_2 AI\ Patents_i +$$

$$Controls + CPC \times Month\ FE + Industry \times Month\ FE + \varepsilon_i. \qquad (4)$$

The results of this dynamic model for non-IT sectors are presented in Figure 4. Consistent with our findings satisfying the parallel trends assumption, the value premium of AI innovations in the pre-period is not statistically different from the last 12 months before the passage of AIPA.

4.4.3 TensorFlow and the Value Premium of AI Innovations in Application Sectors

In addition to policies within the patenting system that broaden and accelerate innovation disclosures, open-sourcing critical innovation could also serve as another policy on the public use of prior innovation, that facilitates follow-on innovation. Specifically, as argued in *H3b*, the decision to open-source important AI infrastructure facilitates knowledge spillovers of AI technologies to downstream (application) sectors which consequently, increases the value premium of AI innovations in these sectors. To examine this hypothesis, we use Google's decision to open-source TensorFlow in November 2015 as an exogenous shock that increased knowledge spillovers in the application of AI technologies in non-IT firms. In particular, prior work shows that the release of TensorFlow stands as a landmark development that reduced barriers to learning ML techniques, and increased the value of AI assets in firms (Rock, 2022).

For this set of analyses, we focus on monthly data in the six-year period centered on Tensorflow's initial release in November 2015, spanning from November 2012 to November 2018. We exclude November 2015 itself as the launch of Tensorflow occurred mid-month. We estimate the following regression based on a sub-sample of 464,783 patents in a patent-month panel for non-IT (application sector) firms:

$$Log\ Patent\ Value_i = \alpha + \gamma_1 AI\ Patents_i \times Post\ TensorFlow_t + \gamma_2 AI\ Patents_i + Controls + CPC \times Month\ FE + Industry \times Month\ FE + \varepsilon_i. \quad (5)$$

The primary variables are defined in the same way as those in Equation (1) and we include the same set of control variables. $Post\ TensorFlow$ is an indicator variable equal to 1 for periods after the initial release of TensorFlow in November 2015 and 0 otherwise. To account for the more rapidly evolving technological trends within this shorter timeframe, we incorporate a more detailed fixed effect structure, including subsection-level CPC technology classes interacted with grant month fixed effects ($CPC \times Month\ FE$) and 3-digit SIC industry groups interacted with grant month fixed effects ($Industry \times Month\ FE$).

Table 9 reports the results of the DiD model in Equation 5. Consistent with *H3b*, we find that the release of TensorFlow is associated with a rise in the value premium of AI patents relative to non-AI patents for non-IT firms. Specifically, Column (1), which includes technology group-month FE and industry-month FE, shows that the post-TensorFlow AI patents in these firms are 2.4% more valuable than AI patents granted prior to TensorFlow. Column (2), which includes the logarithm of forward citations and R&D intensity as controls, also shows that AI patents that are granted after TensorFlow are 2.2% more valuable compared to non-AI patents in non-IT firms. Overall, these findings are in line with our expectation that the release of TensorFlow benefits the downstream development of AI technologies in application sectors (or non-IT industries).

The causal interpretation of a DiD model hinges on the validity of the parallel trends assumption. To assess parallel trends, we estimate a dynamic model by including a set of dummy variables that indicate each year before and after the release of TensorFlow and use the last 12 months before TensorFlow as the benchmark year (Nov 2014 to Oct 2015):

$$Log\ Patent\ Value_i = \alpha + \sum_{k=-2,-1}^{1,2,3} \gamma^k AI\ Patents_i \times 1_{Year_k=1} + \gamma_2 AI\ Patents_i +$$

$$Controls + CPC \times Month\ FE + Industry \times Month\ FE + \varepsilon_i . \qquad (6)$$

The results of this dynamic model for non-IT sectors are presented in Figure 5. Consistent with our findings satisfying the parallel trends assumption, the value premium of AI innovation in the pre-period is not statistically different from the 12-months before the release of TensorFlow.

5 Conclusion

General purpose technologies, such as AI, have driven wide-spread and sustained periods of growth throughout economic history. Consequently, the recent development of AI technologies has led many to speculate on the large potential value of these technologies. Thus, in this study, we analyze the value of AI innovation as it diffuses across general and application sectors throughout the economy.

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 9%. This value premium also increases over time, and is mainly driven by sectors and firms where AI exhibits stronger technical benefits, after controlling for changes in overall interest and investor uncertainty over AI technologies.

Moreover, we find consistent evidence of specialization in the development of general (application-specific) AI technologies as these innovations tend to be more valuable in the IT (non-IT) sectors. Due to this specialization, we predict that innovation policies that facilitate knowledge spillovers are key to unlocking the value in downstream AI innovations in application sectors. Consistent with our predictions, we find that the passage of the patent publication rule in AIPA and the open sourcing of TensorFlow are associated with a 5% and 2% increase, respectively, in the value premium of AI innovation in application sectors.

Taken together, our findings provide important practitioner insights on the value of AI technologies. Specifically, our analysis reveals a value premium in AI innovations, due to the knowledge spillovers and commercialization potential of AI. Moreover, we provide further insight on policies that strengthen the knowledge spillovers underpinning AI technological development, by shedding light on the innovation disclosure and public-use policies that increase the value of AI technologies in downstream, application sectors.

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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), developed by 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.
Log Patent Value	The natural logarithm of patent value, adjusted to 1982 (million) dollars using the CPI, developed by Kogan et al. (2017)
Log Citations	The natural logarithm of 1 plus the number of forward citations the patent receives.
Log Firm Size	The natural logarithm of a firm's market capitalization on the day before the patent issue date.
Log Return Volatility	The natural logarithm of the standard deviation of a firm's daily stock returns in a year.
R&D Intensity	Average R&D expenses scaled by lagged total assets over a rolling 5-year period.
IT	An indicator variable equal to 1 for patents assigned to firms within the Information Technology (IT) industry, designated by a 3-digit SIC code of 737 (Computer and data processing services).
Time Trend	The number of years relative to the starting year of the sample period (1995).
High AI Exposure (Industry)	An indicator variable equal to 1 for patents assigned to firms in industries with above median AI Industry Exposure (AIIE). AIIE is developed by Felten et al. (2021), based on aggregated occupational-level exposure to AI within an industry.
High AI Exposure (Firm)	An indicator variable equal to 1 for patents assigned to firms with above median 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*.
Overall AI Interest	Google trend scores of search term "Artificial Intelligence" by month (available from January 2004), scaled by 100.
PatentValue Volatility	The standard deviation of AI patent values in a CPC technology group in a year.
General Patents	An indicator variable equal to 1 if a patent receives citations from at least three distinct Cooperative Patent Classification (CPC) groups.
Application-Specific Patents	An indicator variable equal to 1 if a patent receives citations from only one CPC group.
Average Citation (AI)	The average forward citations of AI patents granted to the firm in the past five years.
Average Citation (non-AI)	The average forward citations of non-AI patents granted to the firm in the past five years.
Post TensorFlow	An indicator variable equal to 1 for periods after the initial release of TensorFlow in November 2015, and 0 otherwise.
Post AIPA	An indicator variable equal to 1 for periods after the enactment of AIPA in November 2000, 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.
Log # of AI Patents (Equal-Weighted)	The natural logarithm of 1 plus the number of granted AI patents in a year.
Log # of Software Patents (Equal-Weighted)	The natural logarithm of 1 plus the number of granted software patents in a year.
Log # of All Patents (Equal-Weighted)	The natural logarithm of 1 plus the number of all granted patents in a year.
Log # of AI Patents (Value-Weighted)	The natural logarithm of 1 plus the weighted average of granted AI patents in a year, where the weight is determined by the market value of AI patents.
Log # of Software Patents (Value-Weighted)	The natural logarithm of 1 plus the weighted average of granted software patents in a year, where the weight is determined by the market value of software patents.
Log # of All Patents (Value-Weighted)	The natural logarithm of 1 plus the weighted average of all granted patents in a year, where the weight is determined by the market value of granted patents.

Figure 1. Time Trends of AI Innovation

This figure presents the trends of AI innovation from 1995 to 2020. The blue line represents the annual number of granted AI patents, while the red line illustrates the percentage of granted AI patents relative to the total number of granted patents filed each year.

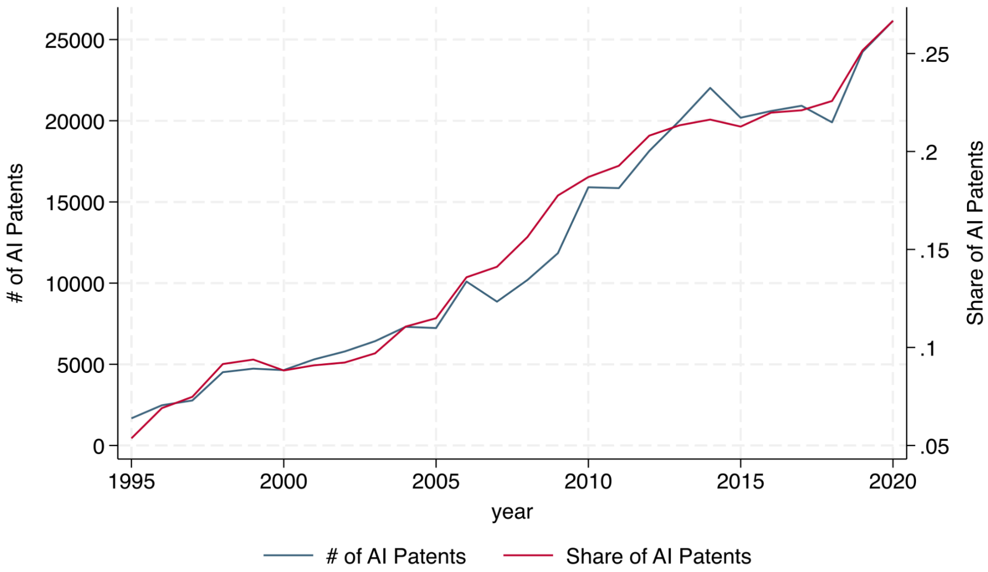

Figure 2. Cumulative Ratio of AI Patents to All Patents by SIC Divisions across Years

This figure illustrates the cumulative ratio of granted AI patents to all granted patents by nine SIC divisions across years, from 1995 to 2020. Darker (lighter) colors indicate higher (lower) values. We present 9 industry divisions from SIC codes, namely IT (SIC 737), Retail and Wholesale Trade (SIC 5000-5999), Finance (6000-6799), Non-IT Services (SIC 7000-8999 except SIC 737), Transportation (SIC 4000-4999) , Manufacturing (SIC 2000-3999), Mining (1000-1499), Agriculture (0100-0999), Construction (1500-1799).

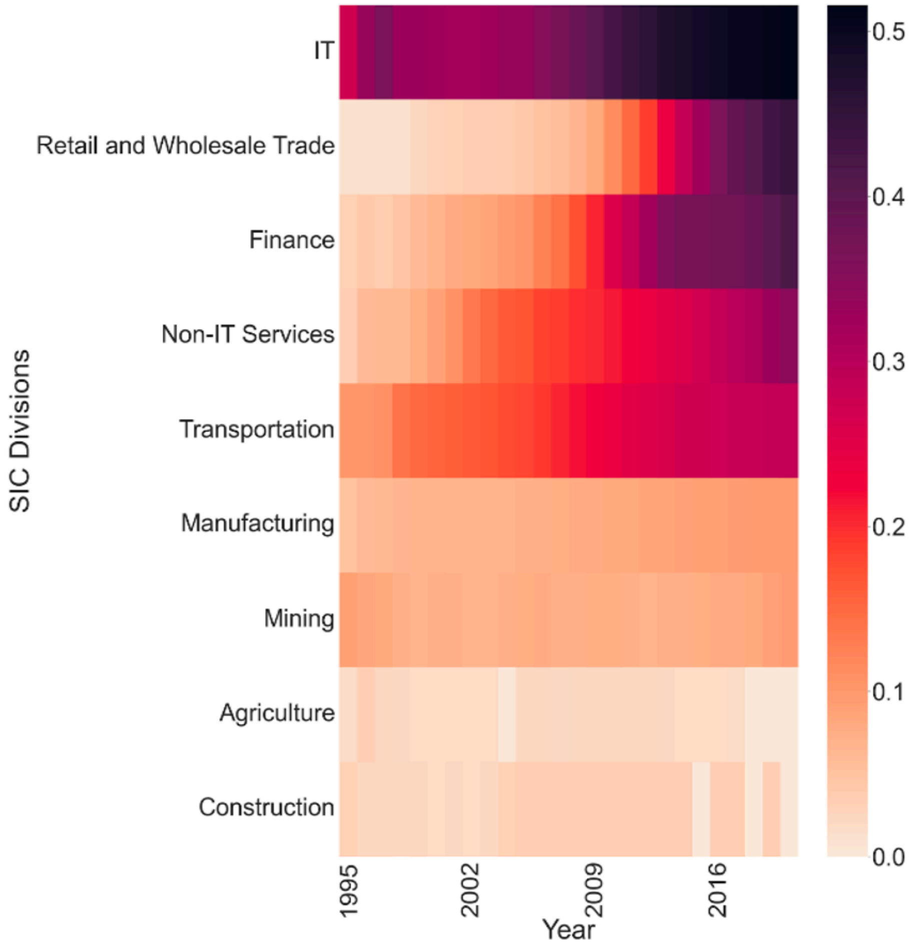

Figure 3. AI Patents Value Premium by Time Periods

This figure presents the estimated β_1 values from Equation (1), which capture the market value premium of AI patents compared to non-AI patents across five distinct periods: 1995-2000, 2001-2005, 2006-2010, 2011-2015, and 2016-2020. Accompanying each estimate are the corresponding 95% confidence intervals.

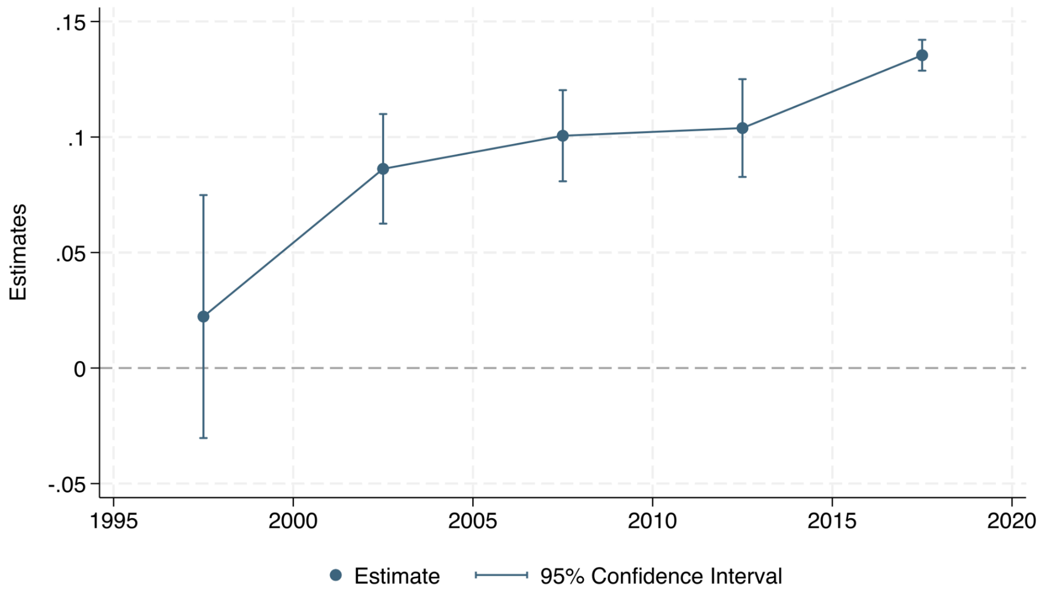

Figure 4. Parallel Trends: AI Patents Market Value in Non-IT Industries Around the Enactment of AIPA

This figure illustrates the estimated γ^k values from Equation (4) for the period centered on AIPA's enactment in November 2000. These values capture the evolving impact of AIPA on the market value of AI patents over time. Each period is distinctly labeled, with the year immediately preceding AIPA's enactment (November 1999 - October 2000) serving as the benchmark, along with corresponding 90% confidence intervals. A vertical red dashed line denotes the initial release of AIPA for clarity.

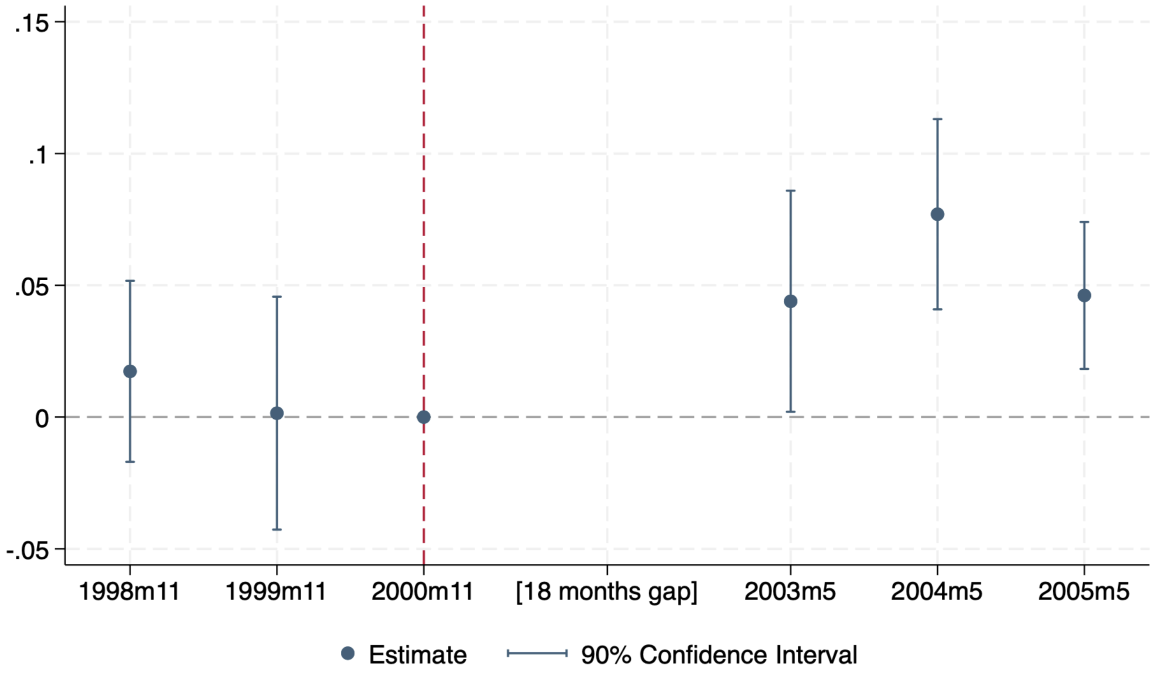

Figure 5. Parallel Trends: AI Patents Market Value in Non-IT Industries Around the Initial Release of TensorFlow

This figure illustrates the estimated γ^k values from Equation (6) for the six-year period centered on TensorFlow's initial release in November 2015. These values capture the evolving impact of TensorFlow on the market value of AI patents over time. Each period is distinctly labeled, with the year immediately preceding TensorFlow's initial release (November 2014 - October 2015) serving as the benchmark, along with corresponding 90% confidence intervals. A vertical red dashed line denotes the initial release of TensorFlow for clarity.

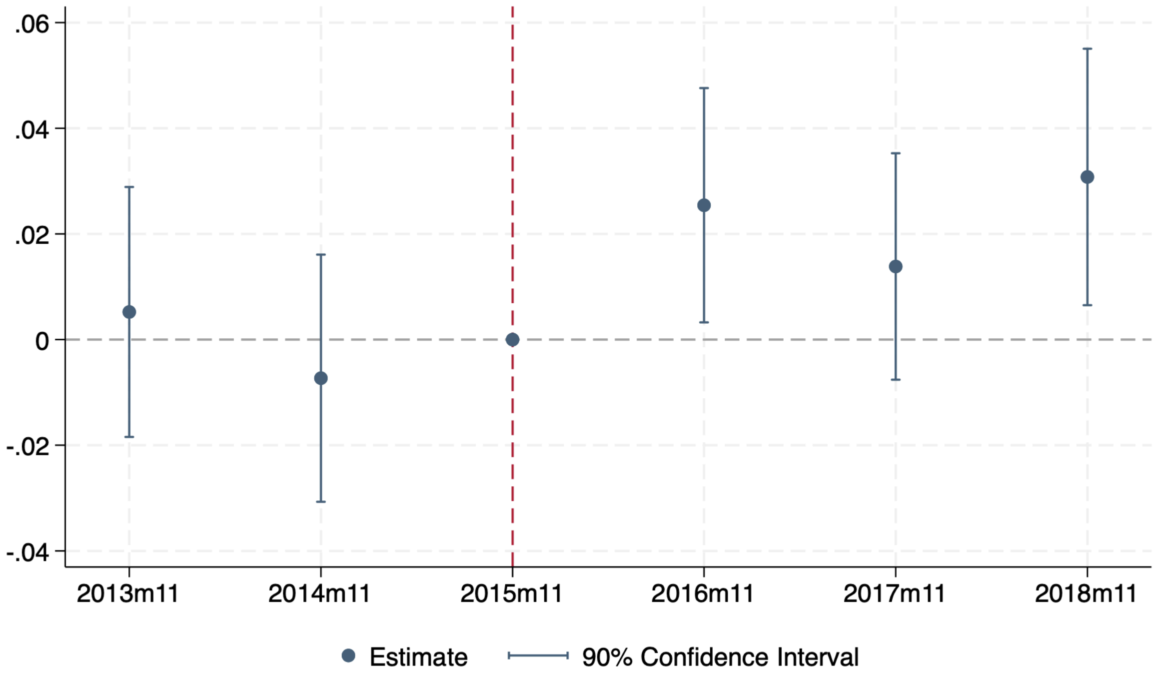

Table 1. AI Patenting Across Industries

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	85	4	9.76%
10	Metal Mining	17	4	1.61%
13	Oil And Gas Extraction	1994	20	3.57%
16	Heavy Construction Other Than Building Construction Contractors	48	3	6.12%
20	Food And Kindred Products	92	18	5.92%
21	Tobacco Products	36	3	13.64%
24	Lumber And Wood Products, Except Furniture	52	2	3.33%
25	Furniture And Fixtures	256	15	25.00%
26	Paper And Allied Products	435	15	11.81%
27	Printing, Publishing, And Allied Industries	178	19	11.95%
28	Chemicals And Allied Products	2284	219	11.62%
29	Petroleum Refining And Related Industries	963	20	23.53%
30	Rubber And Miscellaneous Plastics Products	581	10	8.20%
32	Stone, Clay, Glass, And Concrete Products	165	7	9.33%
33	Primary Metal Industries	37	7	3.93%
34	Fabricated Metal Products, Except Machinery And Transportation Equipment	389	19	13.19%
35	Industrial And Commercial Machinery And Computer Equipment	41371	266	34.19%
36	Electronic And Other Electrical Equipment And Components, Except Computer Equipment	65277	352	32.62%
37	Transportation Equipment	12607	64	23.19%
38	Measuring, Analyzing, And Controlling Instruments; Photographic, Medical And Optical Goods; Watches And Clocks	13273	263	29.13%
39	Miscellaneous Manufacturing Industries	467	21	15.33%
40	Railroad Transportation	21	3	11.54%
42	Motor Freight Transportation And Warehousing	324	6	7.23%
45	Transportation By Air	95	8	8.60%
47	Transportation Services	24	4	6.45%
48	Communications	14322	77	12.05%
49	Electric, Gas, And Sanitary Services	134	27	6.32%
50	Wholesale Trade-durable Goods	133	18	5.50%
51	Wholesale Trade-non-durable Goods	56	9	4.62%
52	Building Materials, Hardware, Garden Supply, And Mobile Home Dealers	15	1	3.57%
53	General Merchandise Stores	351	3	4.69%
54	Food Stores	12	1	1.20%
57	Home Furniture, Furnishings, And Equipment Stores	31	4	6.67%

59	Miscellaneous Retail	8134	17	4.78%
60	Depository Institutions	4000	30	1.86%
61	Non-depository Credit Institutions	1980	10	4.24%
62	Security And Commodity Brokers, Dealers, Exchanges, And Services	1039	23	10.00%
63	Insurance Carriers	1212	19	4.68%
64	Insurance Agents, Brokers, And Service	14	3	3.90%
67	Holding And Other Investment Offices	1708	20	0.33%
73	Business Services	130645	570	23.77%
78	Motion Pictures	220	4	3.51%
79	Amusement And Recreation Services	389	9	5.52%
80	Health Services	141	17	5.72%
82	Educational Services	36	6	6.12%
87	Engineering, Accounting, Research, Management, And Related Services	2573	46	15.33%

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 1,857,451 patent observations for our patent-level analyses that are described in Panel A and 93,464 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	1,857,451	0.171	0.377	0.000	0.000	0.000
Patent Value (in millions)	1,857,451	11.454	24.299	0.606	3.671	11.269
# of Forward Citations	1,857,451	12.382	28.796	0.000	3.000	11.000
Market Value (in billions)	1,857,451	68.530	151.449	1.894	11.388	77.814
Return Volatility	1,857,451	4.731	6.749	1.368	2.571	5.225
R&D Intensity	1,857,451	0.068	0.060	0.026	0.056	0.093
IT	1,857,451	0.137	0.344	0.000	0.000	0.000
Relative Year	1,857,451	15.564	7.074	10.000	17.000	22.000
High AI Exposure (Industry)	1,857,451	0.408	0.491	0.000	0.000	1.000
High AI Exposure (Firm)	1,857,451	0.492	0.500	0.000	0.000	1.000
Overall AI Interest	1,413,829	0.257	0.113	0.160	0.210	0.340
PatentValue Volatility	1,857,451	2.840	0.745	2.313	2.813	3.302
General Patents	1,857,451	0.221	0.415	0.000	0.000	0.000
Sector-Focused Patents	1,857,451	0.270	0.444	0.000	0.000	1.000

Panel B. Firm-Year Level Variables

	N	*Mean*	*Std. Dev.*	*p25*	*Median*	*p75*
ROS	93,464	0.035	0.197	-0.006	0.043	0.101
Asset Turnover	93,464	1.017	0.779	0.454	0.842	1.357
# of AI Patents (Equal-Weighted)	93,464	1.535	12.017	0.000	0.000	0.000
# of Software Patents (Equal-Weighted)	93,464	0.848	6.766	0.000	0.000	0.000
# of All Patents (Equal-Weighted)	93,464	12.617	83.150	0.000	0.000	1.000
# of AI Patents (Value-Weighted)	93,464	17.227	155.976	0.000	0.000	0.000
# of Software Patents (Value-Weighted)	93,464	8.912	79.719	0.000	0.000	0.000
# of All Patents (Value-Weighted)	93,464	132.180	950.976	0.000	0.000	0.100

Table 3. Market Value of AI Patents

This table examines the market value premium of AI patents relative to non-AI patents. The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). The main independent variable of interest, *AI Patents*, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, developed by the Artificial Intelligence Patent Dataset (AIPD). CPC×Year and Industry×Year fixed effects are included. Standard errors are clustered by the patent grant year, and *t-statistics* are reported in parenthesis. The unit of observation is at the patent level. 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.: Log Patent Value	(1)	(2)	(3)
AI Patents	0.112***	0.091***	0.087***
	(20.71)	(15.20)	(14.09)
Firm Size	0.903***	0.899***	0.887***
	(86.45)	(84.74)	(80.47)
Return Volatility	1.062***	1.050***	1.041***
	(28.94)	(28.45)	(28.26)
Log Citations		0.080***	0.081***
		(15.47)	(15.74)
R&D Intensity			2.507***
			(5.45)
CPC*Year FE	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes
Observations	1,857,439	1,857,439	1,857,439
Adjusted R^2	0.828	0.829	0.832

Table 4. AI Patents, Forward Citations, and Market Value

This table presents the results of a comparison between the forward citations of AI patents and non-AI patents. In Panel A, the dependent variable, *Log Citations*, is defined as the natural logarithm of 1 plus the number of forward citations the patent receives. The main independent variable of interest, *AI Patents*, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, developed by the Artificial Intelligence Patent Dataset (AIPD). In Panel B, The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). We incorporate an interaction term between AI Patents and Log Citations. CPC×Year and Industry×Year fixed effects are included. Standard errors are clustered by the patent grant year, and *t-statistics* are reported in parenthesis. The unit of observation is at the patent level. 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.

Panel A. Forward Citations of AI Patents

D.V.: Log Citations	(1)	(2)
AI Patents	0.260***	0.260***
	(7.35)	(7.35)
Log Firm Size	0.047***	0.048***
	(12.81)	(13.03)
Log Return Volatility	0.149***	0.149***
	(12.59)	(12.75)
R&D Intensity		-0.102*
		(-2.02)
CPC×Year FE	Yes	Yes
Industry×Year FE	Yes	Yes
Observations	1,857,439	1,857,439
Adjusted R^2	0.432	0.432

Panel B. Market Value of AI Patent Conditional on Forward Citations

D.V.: Log Patent Value	(1)	(2)
AI Patents	0.029***	0.027***
	(8.06)	(8.01)
AI Patents × Log Citations	0.075***	0.075***
	(15.54)	(15.65)
Log Firm Size	0.044***	0.043***
	(5.48)	(4.97)
Log Citations	0.900***	0.887***
	(84.86)	(80.59)
Log Return Volatility	1.049***	1.041***
	(28.46)	(28.27)
R&D Intensity		2.505***
		(5.45)
CPC×Year FE	Yes	Yes
Industry×Year FE	Yes	Yes
Observations	1,857,439	1,857,439
Adjusted R^2	0.829	0.832

Table 5. AI Innovation and Accounting Performance

This table presents the effects of AI innovation on accounting performance across the three years following the patent grant. The dependent variable is Return on Sales (*ROS*) in Panel A and *Asset Turnover* in Panel B. Across all panels, the accounting metric is evaluated at the year after the patent grant in Columns (1) and (4), two years post-patent grant in Columns (2) and (5), and three years after the patent grant in Columns (3) and (6). In Columns (1)-(3), each patent is treated equally, and we count the number of AI patents, software patents, or all granted patents in a year. In Columns (4)-(6), we calculate the market value-weighted average of AI, software, or all granted patents in a year, where the weight is determined by the market value of patents. All the count variables are log-transformed. In all the columns, control variables include firm size, book-to-market ratio, # of , and the ratio of intangible assets to lagged total assets. Firm and Year fixed effects are included in all the columns. Standard errors are double-clustered by firm and fiscal year, and *t-statistics* are reported in parenthesis. The unit of observation is at the firm-year level. 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 significant at 10%, 5%, and 1%, respectively.

Panel A. ROS

	# of Patents			**Value-Weighted Patents**		
	(1)	(2)	(3)	(4)	(5)	(6)
	Forward 1 Year	**Forward 2 Years**	**Forward 3 Years**	**Forward 1 Years**	**Forward 2 Years**	**Forward 3 Years**
AI Patents	0.003	0.009***	0.005*	0.002	0.003***	0.003*
	(1.11)	(2.92)	(1.76)	(1.31)	(2.70)	(1.94)
Software Patents	0.006**	-0.001	-0.001	0.003***	0.001	0.001
	(2.27)	(-0.40)	(-0.43)	(2.65)	(0.52)	(0.72)
All Patents	-0.003	-0.002	0.001	-0.001	-0.001	0.001
	(-1.59)	(-0.95)	(0.38)	(-1.22)	(-0.75)	(0.45)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,464	81,672	71,990	93,464	81,672	71,990
Adjusted R^2	0.471	0.455	0.449	0.471	0.455	0.449

Panel B. Asset Turnover

	# of Patents			Value-Weighted Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
	Forward 1 Year	**Forward 2 Years**	**Forward 3 Years**	**Forward 1 Years**	**Forward 2 Years**	**Forward 3 Years**
AI Patents	-0.007	-0.004	-0.012**	-0.002	-0.001	-0.002
	(-1.38)	(-0.65)	(-2.07)	(-0.73)	(-0.22)	(-0.76)
Software Patents	0.002	-0.007	-0.001	0.002	-0.001	0.001
	(0.24)	(-1.05)	(-0.19)	(0.62)	(-0.45)	(0.38)
All Patents	0.002	0.006	0.010**	0.001	0.004	0.004*
	(0.48)	(1.60)	(2.39)	(0.58)	(1.63)	(1.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	93,464	82,962	72,888	93,464	82,962	72,888
Adjusted R^2	0.871	0.876	0.879	0.871	0.876	0.879

Table 6. Time-Trend Analysis of the Value Premium of AI Innovations

This table reports the drivers of the time-trend in the value premium of AI patents over time. The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). *Time Trend* represents the number of years relative to the starting year of the sample period (1995). AI exposure is measured based on occupational-level exposure to AI, either at the industry level in Columns (2) - (3) or at the firm level in Columns (4) - (5). *Overall AI Interest* is measured by Google trend scores of search term "Artificial Intelligence" by month, with data available since January 2004. *PatentValue Volatility* is defined as the standard deviation of AI patent values in a CPC technology group in a year. CPC×Year and Industry×Year fixed effects are included. Standard errors are clustered by the patent grant year, and *t-statistics* are reported in parenthesis. 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.

		High AI Exposure (Industry)		High AI Exposure (Firm)	
	(1)	(2)	(3)	(4)	(5)
*AI Patents * Time Trend*	0.004***	0.002*	-0.001	0.001	-0.001
	(5.42)	(1.86)	(-0.43)	(0.45)	(-0.37)
*High AI Exposure * AI Patents * Time Trend*		0.005**	0.005**	0.006**	0.007**
		(2.01)	(2.31)	(2.38)	(2.68)
*AI Patents * Overall AI Interest*			0.127		0.029
			(1.32)		(0.29)
*AI Patents * PatentValue Volatility*			0.024**		0.051**
			(2.22)		(2.51)
*High AI Exposure * AI Patents*		0.154***	0.132**	-0.038	-0.065
		(3.41)	(2.91)	(-0.67)	(-1.17)
Overall AI Interest			-0.046		-0.013
			(-0.22)		(-0.06)
PatentValue Volatility			0.145***		0.194***
			(8.83)		(10.82)
AI Patents	0.009	-0.081***	-0.139***	0.043	-0.084
	(0.57)	(-4.23)	(-4.77)	(1.14)	(-1.30)
Firm Size	0.887***	0.847***	0.846***	0.895***	0.894***
	(80.46)	(53.32)	(53.18)	(68.94)	(68.55)
ReturnVolatility	1.041***	0.978***	0.976***	1.057***	1.055***
	(28.27)	(18.56)	(18.49)	(16.73)	(16.67)
Log Citations	0.081***	0.092***	0.092***	0.099***	0.099***
	(16.03)	(24.49)	(23.74)	(19.34)	(18.54)
R&D Intensity	2.508***	3.336***	3.354***	3.959***	4.004***
	(5.45)	(8.61)	(8.63)	(10.06)	(10.19)
CPC*Year FE	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,857,439	1,413,819	1,413,819	985,010	985,010
Adjusted R^2	0.832	0.813	0.814	0.814	0.815

Table 7. Value Premium of AI Innovation Across General and Application-Specific Innovations

This table presents the market value premiums of AI patents, across patents that are classified as general or application-specific. The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). In Columns (1) and (2), *General Patents* is defined as an indicator variable equal to 1 if a patent receives citations from at least three distinct CPC groups. In Columns (3) and (4), *Application-Specific Patents* is defined as an indicator variable equal to 1 if a patent receives citations from only one CPC group. Standard errors are clustered by the patent grant year, and *t-statistics* is reported in parenthesis. All variables are winsorized at the top and bottom 1% of the cross-sectional distribution and defined as in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

	General Patents		**Application-Specific Patents**	
	(1)	(2)	(3)	(4)
D.V.: Log Patent Value	*IT*	*Non-IT*	*IT*	*Non-IT*
General Patents×AI Patents	0.038**	-0.042***		
	(2.39)	(-3.80)		
Application-Specific Patents × AI Patents			-0.038**	0.027**
			(-2.11)	(2.78)
[Difference (IT minus non-IT)]	*0.080****		*-0.065****	
	(4.13)		*(-3.18)*	
General Patents	-0.023*	0.041***		
	(-2.05)	(10.83)		
Application-Specific Patents			-0.051**	-0.028***
			(-2.72)	(-7.89)
AI Patents	0.132***	0.016*	0.151***	-0.006
	(5.91)	(1.90)	(6.48)	(-1.16)
Log Firm Size	0.574***	0.931***	0.574***	0.931***
	(11.31)	(98.69)	(11.31)	(98.66)
Log Return Volatility	1.162***	0.949***	1.160***	0.950***
	(12.45)	(32.31)	(12.45)	(32.32)
Log Citations	0.104***	0.058***	0.093***	0.064***
	(7.11)	(10.02)	(6.49)	(11.86)
R&D Intensity	7.271***	-0.175	7.256***	-0.177
	(11.48)	(-0.37)	(11.45)	(-0.37)
CPC×Year FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
Observations	140,128	993,507	140,128	993,507
Adjusted R^2	0.579	0.862	0.580	0.862

Table 8. AIPA and the Value Premium of AI Innovation in Non-IT Industries

This table examines the effects of the enactment of AIPA on the market value premiums of AI patents relative to non-AI patents for firms in non-IT industries. The sample includes periods centered around the enactment of AIPA in November 2000, spanning from November 1997 to May 2005 and excluding the first 18 months after AIPA. The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). The main independent variable of interest, *AI Patents*, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, developed by the Artificial Intelligence Patent Dataset (AIPD). *Post AIPA* is defined as an indicator variable equal to 1 for periods after the enactment of AIPA in November 2000, and 0 otherwise. CPC×Month and Industry×Month fixed effects are included. Standard errors are clustered by the patent grant month, and *t-statistics* is reported in parenthesis. The unit of observation is at the patent level. 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.

	(1)	(2)
*Post AIPA * AI Patents*	0.052***	0.055***
	(3.60)	(3.96)
AI Patents	-0.020*	-0.046***
	(-1.97)	(-4.65)
Log Firm Size	0.943***	0.953***
	(184.07)	(189.94)
Log Return Volatility	1.037***	1.016***
	(76.53)	(77.71)
Log Citations		0.049***
		(25.07)
R&D Intensity		-2.910***
		(-13.76)
CPC×Month FE	Yes	Yes
Industry×Month FE	Yes	Yes
Observations	327,386	327,386
Adjusted R^2	0.898	0.900

Table 9. TensorFlow and the Value Premium of AI Innovation in Non-IT Industries

This table examines the effects of TensorFlow's initial release on the market value premiums of AI patents relative to non-AI patents for firms in non-IT industries. The sample includes a six-year period centered around the initial release of TensorFlow in November 2015. The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). The main independent variable of interest, *AI Patents*, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, developed by the Artificial Intelligence Patent Dataset (AIPD). *Post TensorFlow* is defined as an indicator variable equal to 1 for periods after the initial release of TensorFlow in November 2015, and 0 otherwise. CPC×Month and Industry×Month fixed effects are included. Standard errors are clustered by the patent grant month, and *t-statistics* is reported in parenthesis. The unit of observation is at the patent level. 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.

	(1)	(2)
*Post TensorFlow * AI Patents*	0.024***	0.022***
	(3.05)	(2.70)
AI Patents	0.002	-0.005
	(0.30)	(-0.84)
Log Firm Size	0.922***	0.910***
	(309.49)	(288.27)
Log Return Volatility	0.910***	0.891***
	(66.79)	(63.32)
Log Citations		0.066***
		(27.18)
R&D Intensity		1.505***
		(12.61)
CPC×Month FE	Yes	Yes
Industry×Month FE	Yes	Yes
Observations	464,783	464,783
Adjusted R^2	0.847	0.849

Internet Appendix for The Value of AI Innovations

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Figure IA1. Intensive Margin and Extensive Margin of AI Innovation by Years

This figure presents the intensive margin and extensive margin of AI Innovation from 1995 to 2020. The blue line plots the average number of granted AI patents per firm (intensive margin) and the red line plots the proportion of public firms granted at least one AI patent each year (extensive margin).

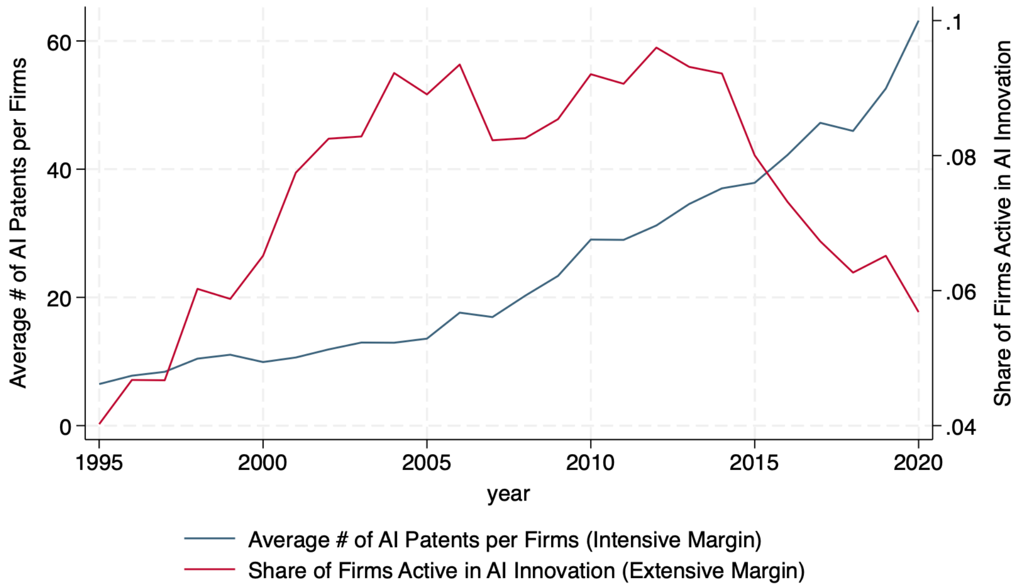

Figure IA2. AI Patents Value Premium by AI Technology Components

This figure presents the estimated β_1 values from Equation (1), which measures the market value premium of AI patents compared to non-AI patents for each of the eight 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).

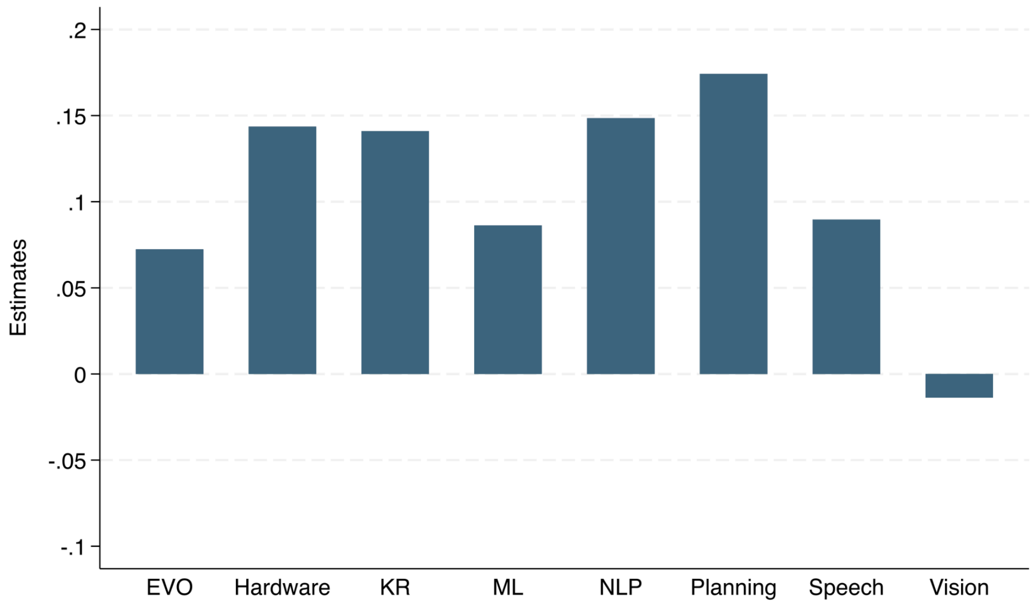

Table IA1. Determinants of AI Innovation

This table reports the results of analysis on the determinants of AI innovation. The dependent variable is the ratio of subsequently granted AI patents applied in a year to the total number of patent applications. Industry×Year fixed effects are included in Column (2). Both Firm and Industry×Year fixed effects are incorporated in Columns (3). Value-Weighted Patent Stocks (AI/NonAI) is the natural logarithm of 1 plus the market value-weighted number of AI/NonAI patents granted to the firm in the past 5 years. Standard errors are double clustered by the firm and year, and *t-statistics* are reported in parenthesis. 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.

D.V.: % of AI Patents	(1)	(2)	(3)
Value-Weighted Patent Stocks (AI)	0.043***	0.041***	0.042***
	(14.75)	(14.87)	(14.67)
Value-Weighted Patent Stocks (NonAI)	-0.008***	-0.009***	-0.009***
	(-8.45)	(-9.90)	(-9.53)
IT	0.086***		
	(12.03)		
R&D Intensity	0.034***	0.036***	0.036***
	(2.82)	(2.97)	(2.95)
Log Assets	0.002**	0.004***	0.004***
	(2.24)	(3.96)	(4.00)
Sales Growth	0.007***	0.005***	0.006***
	(3.53)	(2.98)	(3.48)
Leverage	-0.030***	-0.027***	-0.029***
	(-8.59)	(-8.32)	(-8.48)
External Finance	0.003	0.007***	0.008***
	(0.92)	(3.46)	(3.61)
CAPX	-0.010	0.003	0.003
	(-1.30)	(0.43)	(0.49)
Age	-0.002	-0.001	-0.001
	(-1.61)	(-0.88)	(-0.81)
Sales Shares	-0.002	-0.007	-0.010
	(-0.38)	(-1.15)	(-1.49)
Industry FE	No	Yes	No
Year FE	No	Yes	No
Industry×Year FE	No	No	Yes
Observations	118,366	118,366	118,366
Adjusted R^2	0.168	0.181	0.166

Table IA2. Robustness Analysis: Poisson Regression

This table replicates the main findings using the fixed-effect Poisson model. The dependent variables are patent value (in millions), adjusted to 1982 million dollars using the CPI, in Columns (1) - (2) and the number of forward citations in Columns (3) - (4). The main independent variable of interest, *AI Patents*, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, developed by the Artificial Intelligence Patent Dataset (AIPD). We include CPC×Year and Industry×Year fixed effects. Standard errors are clustered by the patent grant year, and *t-statistics* is reported in parenthesis. All variables are winsorized at the top and bottom 1% of the cross-sectional distribution and defined as in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

D.V.:	**Patent Value (in millions)**		**# of Forward Citations**	
	(1)	(2)	(3)	(4)
AI Patents	0.059***	0.045***	0.487***	0.488***
	(8.69)	(8.00)	(18.79)	(18.84)
Log Firm Size	0.676***	0.669***	0.066***	0.069***
	(39.17)	(39.38)	(23.41)	(22.74)
Log Return Volatility	0.770***	0.760***	0.225***	0.222***
	(20.37)	(19.94)	(24.93)	(24.83)
Log Citations		0.044***		
		(13.58)		
R&D Intensity		1.045***		-0.611***
		(3.52)		(-7.79)
CPC×Year FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
Observations	1,857,439	1,857,439	1,857,174	1,857,174
Adjusted R^2	0.666	0.667	0.400	0.400

Table IA3. Robustness Analysis: IHS-transformation

This table replicates the main findings using IHS-transformed variables. The dependent variables are either the IHS-transformed patent value (in millions), adjusted to 1982 million dollars using the CPI, in Columns (1) - (2) or the IHS-transformed number of forward citations in Columns (3) - (4). The main independent variable of interest, *AI Patents*, is an indicator variable equal to 1 if a patent is categorized under one or more of the eight AI technology components, developed by the Artificial Intelligence Patent Dataset (AIPD). We include CPC×Year and Industry×Year fixed effects. Standard errors are clustered by the patent grant year, and *t-statistics* is reported in parenthesis. All variables are winsorized at the top and bottom 1% of the cross-sectional distribution and defined as in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

D.V.:	**$\sinh^{-1}$(Patent Value)**		**$\sinh^{-1}$(Citations)**	
	(1)	(2)	(3)	(4)
AI Patents	0.070***	0.054***	0.297***	0.297***
	(15.59)	(11.58)	(7.89)	(7.89)
$\sinh^{-1}$(Firm Size)	0.537***	0.530***	0.056***	0.056***
	(50.41)	(49.90)	(13.91)	(14.24)
$\sinh^{-1}$(Return Volatility)	0.548***	0.537***	0.190***	0.190***
	(19.54)	(19.50)	(14.87)	(15.02)
$\sinh^{-1}$(Citations)		0.048***	0.056***	0.056***
		(15.45)	(13.91)	(14.24)
R&D Intensity		0.864***	0.190***	0.190***
		(4.22)	(14.87)	(15.02)
CPC×Year FE	Yes	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes	Yes
Observations	1,857,439	1,857,439	1,857,174	1,857,174
Adjusted R^2	0.761	0.763	0.434	0.434

Table IA4. AI Patents Value Premium: Firm-level Heterogeneity

This table examines the firm-level heterogeneity in the AI patent value premium by studying the market value premiums of AI patents conditional on historical innovation quality. The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). In Column (1), *Historical Quality* is measured by the average forward citations received by all the patents granted in the rolling past 5 years. In Column (2), *Historical Quality* is measured by the average forward citations received by AI patents granted in the rolling past 5 years. We include CPC×Year and Industry×Year fixed effects. Standard errors are clustered by the patent grant year, and *t-statistics* are reported in parenthesis. The unit of observation is at the patent level. 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.

	(1)	(2)
D.V.: Log Patent	**Average Citation (All)**	**Average Citation (AI)**
Historical Quality×AI Patents	0.034**	0.052***
	(2.77)	(4.15)
Historical Quality	0.050***	-0.089***
	(3.00)	(-15.07)
AI Patents	-0.012	-0.073**
	(-0.39)	(-2.47)
Log Firm Size	0.882***	0.899***
	(73.35)	(79.23)
Log Return Volatility	1.045***	1.019***
	(28.70)	(27.92)
Log Citations	0.078***	0.082***
	(17.83)	(15.31)
R&D Intensity	2.324***	2.861***
	(5.20)	(7.22)
CPC×Year FE	Yes	Yes
Industry×Year FE	Yes	Yes
Observations	1,857,439	1,857,439
Adjusted R^2	0.832	0.834

Table IA5. AI Patents Value Premium: Explorative vs. Exploitative

This table presents the value premiums of AI patents across patents that are categorized as exploratory or exploitative. The dependent variable, *Log Patent Value*, is defined as the natural logarithm of patent value, adjusted to 1982 million dollars using the CPI, developed by Kogan et al. (2017). In Column (1), *Explorative Patents* is defined as an indicator variable equal to 1 if at least 80% of the backward citations of the patent are not from existing knowledge, which includes all of the patents that the firm produced and all of the patents that were cited by the firm's patents filed over the past five years. In Column (2), *Exploitative Patents* is defined as an indicator variable equal to 1 if at least 80% of the backward citations of the patent are from existing knowledge. We include CPC×Year and Industry×Year fixed effects. Standard errors are clustered by the patent grant year, and *t-statistics* is reported in parenthesis. All variables are winsorized at the top and bottom 1% of the cross-sectional distribution and defined as in Appendix A. Coefficients marked with *, **, and *** are statistically significant at 10%, 5%, and 1%, respectively.

	(1)	(2)
D.V.: Log Patent Value	**Explorative Patents**	**Exploitative Patents**
Explorative Patents×AI Patents	0.118***	
	(11.99)	
Exploitative Patents×AI Patents		-0.084***
		(-5.55)
Explorative Patents	0.158***	
	(16.95)	
Exploitative Patents		-0.038***
		(-6.05)
AI Patents	0.068***	0.131***
	(12.08)	(10.24)
Log Firm Size	0.890***	0.888***
	(81.99)	(81.10)
Log Return Volatility	1.039***	1.042***
	(28.47)	(28.35)
Log Citations	0.086***	0.083***
	(17.09)	(16.45)
R&D Intensity	2.490***	2.493***
	(5.47)	(5.44)
CPC×Year FE	Yes	Yes
Industry×Year FE	Yes	Yes
Observations	1,857,439	1,857,439
Adjusted R^2	0.833	0.832