AI Patents

Abstract

This paper investigates the impact of artificial intelligence (AI) innovation development on firm outcomes, industry concentration, and social returns. Using a comprehensive dataset of AI patents from the U.S. Patent and Trademark Office, we find that, compared to non-AI innovation, AI patents are mainly used to enhance firms' existing capabilities rather than to explore new technologies — i.e., they are more exploitative and less explorative. They are associated with lower firm growth and profitability than non-AI. Despite lower private returns, AI innovations act as a general-purpose technology, generating significant knowledge spillovers across various technological fields, leading to positive externalities and higher social returns. Additionally, AI innovations contribute to increased industry growth and concentration. The technological significance of AI innovation likely stems from basic science.

Keywords: Artificial Intelligence, Patents, Innovation, Knowledge Spillover, Firm Growth, Social Returns, Competition

JEL: G30, G41, L21, Q50

1 Introduction

Recent advancements in artificial intelligence (AI) have sparked significant debate about their impact on firms, industries, and the broader economy. While existing studies in finance and economics primarily focus on AI adoption and highlight its substantial benefits for firm growth and productivity (e.g., Babina, Fedyk, He, and Hodson, 2024; Czarnitzki, Fernández, and Rammer, 2023), a notable gap remains in the literature concerning the AI development process itself. Understanding when firms choose to invest in AI technology development, the characteristics of AI innovation, its effects on inventing firms, and its externalities is crucial. These insights are essential for informing innovation policy and fostering more effective AI development.

Leveraging a comprehensive dataset of AI patents from the US Patent and Trademark Office (USPTO), we document key characteristics that distinguish AI patents. Notably, AI patents are more deeply rooted in existing knowledge, citing a greater number of prior arts, with a strong emphasis on existing AI technologies. This suggests that AI operates as a specialized, niche field with limited cross-disciplinary integration during its development. AI patents tend to be more exploitative than explorative (March, 1991), as firms predominantly use AI to enhance and build upon existing technologies rather than to explore new areas.

Despite this narrow initial focus, AI patents show remarkable technological significance. On average, they receive 42% more forward citations and are significantly more likely to be classified as breakthroughs, according to the metric developed by Kelly, Papanikolaou, Seru, and Taddy (2021), when compared to non-AI patents produced by the same firm within the same technological domain. This finding indicates that AI innovations, despite their specialized nature, generate considerable knowledge spillovers across diverse technological fields, reinforcing the idea of AI as a general-purpose technology with broad and far-reaching impacts.

To further understand the sources of AI's technological significance, we investigate its novelty by leveraging the popular measure developed by Verhoeven, Bakker, and Veugelers (2016). The innovation literature suggests that novelty can arise from three primary sources: first, the recombination of existing knowledge to create new capabilities; second, the discovery

of new capabilities within existing technological knowledge; and third, the sourcing of novelty from basic science. Our findings indicate that AI novelty is more likely to be sourced from basic science rather than the first two. AI patents cite 44% more academic papers than non-AI patents, and when combined with the results on forward citations, it suggests that AI acts as a bridge between basic and applied science. However, we do not find that AI has a higher private value to firms when using the market value measure proposed by Kogan, Papanikolaou, Seru, and Stoffman (2017). It seems that shareholders of inventing firms do not experience greater value growth from AI patents than from non-AI patents.

We next investigate the connection between AI innovation and firm growth by building on the extensive literature that suggests a strong relationship between innovation and firm growth (Kogan et al., 2017; Aghion and Howitt, 1992; Klette and Kortum, 2004). Our analysis focuses on how a firm's AI and non-AI innovative activities are related to firm growth, which has an important implication for a firm's innovation strategy. The results reveal that AI innovation significantly contributes less to firm growth (firm profits, sales, capital, labor, and productivity) than non-AI innovation, with growth coefficients for AI being only about one-third of those for non-AI. We also find that firm productivity is only weakly associated with AI innovation, whereas non-AI innovation shows a strong correlation with productivity over a period of up to two years.

This disparity seems to arise from the way firms approach AI development. AI innovations are more exploitative than explorative when compared to non-AI patents. To investigate whether the limited growth contribution of AI innovation is due to its exploitative nature, we conducted further analysis. Our findings indicate that exploitative AI innovation contributes to increases in profit, employment, and productivity, but has little effect on sales and capital growth. This suggests that exploitative AI innovation primarily enhances efficiency within a firm's existing operations rather than enabling entry into new markets. In contrast, explorative AI innovation shows a positive correlation with all measures of firm growth, aligning with the findings of Colombelli, Krafft, and Quatraro (2013). However, the growth coefficients for both AI innovations are still lower than those associated with non-AI patents.

Beyond firm growth, we aim to establish a causal relationship between obtaining AI patents and various firm outcomes by employing a quasi-experimental design inspired by

Farre-Mensa, Hegde, and Ljungqvist (2020). This method exploits the quasi-random assignment of patent applications to examiners, who differ in their propensity to grant patents. The leniency of patent examiners can influence the value of granted patents; however, it is unlikely that this leniency directly correlates with a firm's outcomes, such as its strategies, valuation, or income. This variation allows us to assess the causal impact of securing AI patents on firm outcomes by leveraging the differences in examiners' likelihood to approve patents of similar quality. Specifically, we calculate approval rates for AI patents as per Farre-Mensa, Hegde, and Ljungqvist (2020) and use these rates as an instrumental variable for the number of AI patents granted to a firm.

Our findings suggest that obtaining AI patents is associated with an increase in firm value, as measured by Tobin's Q, but the coefficient magnitude is still one-third of those of non-AI patents. AI innovation does not correspond to higher profitability, which shows that the previous result on profit growth by AI patents is not causal. Additionally, AI patents do not elevate firm risk to the same extent as non-AI patents, likely because AI innovations have wider applicability than non-AI counterparts. We also find that AI patents do not facilitate product innovations, as indicated by no change in trademark registrations, whereas non-AI innovation spurs new trademark registrations. This contrasts with Babina et al. (2024), who suggest that AI adoption boosts product innovation. Our results imply that firms primarily develop AI to enhance existing capabilities, which may not necessarily lead to the creation of entirely new products.

Despite AI's potential as a general-purpose technology — capable of driving subsequent innovations across a wide range of technological fields — we find its impact on expanding firms' operational scope or enabling them to explore new markets and diversify their activities is limited. Using the Hoberg and Phillips (2024); Frésard, Hoberg, and Phillips (2019) 10-K-based measures of firm scope and vertical integration, we find that firms tend to decrease vertical integration and exhibit minimal changes in their operating scope after obtaining AI patents. This indicates that firms are not fully capitalizing on the versatile potential of AI innovations.

Our findings seem to suggest that inventing firms capture only a small fraction of the total value generated by AI innovation, while AI innovation itself creates substantial value

for society at large. Building on the work of Bloom, Schankerman, and Van Reenen (2013), we document the significant technological spillovers that AI contributes to other firms. We find that AI patents generate considerable knowledge spillovers, with these effects being much stronger than those associated with non-AI patents. Firms tend to produce more patents (both AI and non-AI) when they benefit from spillovers originating from other firms' AI patents. This effect is especially pronounced in firms with prior experience in AI development.

To further substantiate our claim that AI innovation generates considerable societal value that the inventing firms do not fully capture, we analyze the social returns of AI and non-AI innovations, following the methodology of Jones and Summers (2021), who evaluated total factor productivity across the economy in relation to R&D expenditures. Our findings demonstrate that the social returns on AI innovation are significantly higher than those on non-AI patents, indicating a greater positive externality associated with AI innovation.

At the industry level, the impact of AI patents on growth and concentration is driven by two opposing forces: positive knowledge spillovers and negative product market spillovers from successful AI innovations, as noted by Bloom, Schankerman, and Van Reenen (2013). Our analysis indicates that AI patents are positively correlated with both industry growth and increased concentration. Interestingly, while AI patenting is associated with decreased concentration among AI firms, it leads to increased concentration among non-AI firms. This suggests that within AI firms, the benefits of knowledge spillovers from AI innovation may outweigh the business-stealing effects. In contrast, within non-AI firms, the business-stealing effects appear to be more dominant, with AI-using firms potentially disrupting and outcompeting other firms, thereby increasing industry concentration.

Our paper makes several contributions to the literature. First, we add to the innovation literature (e.g. Bloom, Schankerman, and Van Reenen, 2013; Jones and Summers, 2021; Lerner, Seru, Short, and Sun, 2024) by documenting the substantial social value of AI innovation, particularly through its knowledge spillovers. On average, AI innovations demonstrate greater technological significance than non-AI innovations, fostering follow-on innovation across a broad range of technological fields, reflecting their role as a general-purpose technology. This technological significance of AI largely stems from its roots in basic science.

We further contribute to the understanding of how AI patents influence the outcomes of

firms that develop AI technologies (Alderucci, Branstetter, Hovy, Runge, and Zolas, 2020). Our findings indicate that AI patents are associated with lower growth and profitability compared to non-AI patents, likely due to the more exploitative nature of AI inventions. This research builds on the work of Babina et al. (2024) by focusing on the effects on firms that invent AI technologies, rather than those that simply adopt them. These results underscore concerns about investing in AI, particularly given its uncertain return on investment (Brynjolfsson and McAfee, 2017).

Finally, we add to the literature on innovation and competition by showing that AI innovation is linked to higher industry growth and increased market concentration (Aghion, Bloom, Blundell, Griffith, and Howitt, 2005; Bloom, Schankerman, and Van Reenen, 2013). Although our results indicate that firms developing AI technologies do not fully capture the economic value generated by their innovations, AI nonetheless produces significant positive externalities for society.

This paper is organized as follows: Section 2 describes the data and presents descriptive statistics on AI and non-AI patents and firms. Section 3 presents the empirical results on characteristics of AI innovation and its impact on firm and industy outcomes. Section 4 concludes.

2 Data

2.1 AI classification and patent data

This study utilizes the Artificial Intelligence Patent Dataset (AIPD) (Giczy, Pairolero, and Toole, 2022), developed by the United States Patent and Trademark Office (USPTO), covering over 13.2 million patents and pre-grant publications (PGPubs) from 1976 through 2020. We briefly describe this data below and refer readers to Giczy, Pairolero, and Toole (2022) for more detailed information.

The AI identification process employed machine learning approaches, utilizing text and citation analysis of patent documents to predict the presence of AI technologies. Initially, key AI patents were identified by specialized USPTO patent examiners who are experts in

the field. This step is crucial, as classifications without expert knowledge often result in higher rates of errors. These seed patents[1] were then used to train a text classifier, which scored each patent publication on its relevance to AI. Following USPTO guidelines, a patent is considered AI-related if it scores above 0.5. The credibility of this classification process stems from the expert identification of seed patents and rigorous verification procedures. These thorough identification and verification processes ensure a high level of accuracy and reliability, distinguishing this method from other classification approaches that often lack such critical steps.

It is important to clarify that the AI in this sample is not limited to the currently popular generative AI (GenAI), such as those classified under machine learning and natural language processing (NLP). The AI captured here encompasses a much broader set, including advanced areas such as NLP, speech, and vision, as well as more traditional AI areas that gained popularity in the last century, such as computational methods and planning/control. The dataset provides classifications for eight AI fields, which are described briefly below:

Machine Learning encompasses a broad range of computational learning models. For example, supervised learning classification models are algorithms that learn to classify observations based on pre-labeled training data. Machine learning techniques include neural networks, fuzzy logic, adaptive systems, probabilistic networks, regression, and intelligent searching.

Evolutionary computation consists of computational methods inspired by natural evolutionary processes. For example, genetic algorithms use methods for selecting algorithm variants by optimizing random mutations to maximize fitness.

Natural language processing (NLP) involves methods for understanding and utilizing data encoded in human language. For instance, language models represent probability distributions of language expressions.

Speech recognition entails methods to interpret a sequence of words from an acoustic signal. One approach, the noisy channel model, uses statistical techniques to determine the

[1]We have provided a list of top-cited seed patents and those most cited patents within their respective AI categories in Appendix Tables A.2 and A.3. Furthermore, Appendix Table A.4 lists the companies receiving the greatest number of AI patents. As expected, the list is dominated by leading technology firms, with IBM on the top, followed by Microsoft, Google, Intel, Samsung, and Amazon. Companies engaged in AI patent filings encompass a broad range of industries.

most likely sequence of words from verbal input by applying Bayes' rule.

Computer vision involves methods to extract and interpret information from visual inputs like images and videos. For instance, edge detection identifies boundaries and borders within an image. Other areas of computer vision include object recognition, image manipulation (such as transformation, enhancement, or restoration), color processing, and image conversion.

Knowledge processing involves methods to represent facts about the world and derive new information from a knowledge base. For example, expert systems typically include a knowledge base and an inference method to generate new facts from that knowledge base.

Planning and control encompass methods to develop and execute plans to achieve specific goals. Key aspects include representing actions and states of the world, reasoning about the effects of actions, and efficiently searching potential plans. Modern control theory focuses on optimizing objectives over time, and includes approaches like stochastic optimal control, which deals with dynamic optimization in uncertain environments. Planning and control also cover data systems for administration and management, adaptive control systems, and models or simulators of systems.

AI hardware focuses on physical components designed to execute artificial intelligence software. For instance, Google developed the Tensor Processing Unit (TPU) to enhance the efficiency of neural network algorithms. AI hardware includes logic circuits, memory, video processors, and solid-state technologies, as well as embedded software that implements various AI technologies like machine learning algorithms.

For patent-level information, we enrich our dataset with the September 2023 release of PatentsView, a resource also developed by the USPTO. To link patents with firms, we utilize the extended data from Kogan et al. (2017) up to 2022, which only establishes links for granted patents. To make our dataset more comprehensive, We link rejected patent applications to firms by matching assignee names with those on granted patents. This method may exclude patent applications from firms that have had all their applications rejected. However, this omission is anticipated to minimally impact our findings, given our focus on publicly traded companies on major stock exchanges where such cases are uncommon.[2]

[2]This assumption is predicated on the observation that the approval rate for patent applications exceeds 50%.

2.2 Firm-level data

Firm-specific information is sourced from the CRSP-Compustat Merged (CCM) dataset. Firm ownership data is obtained from the Refinitiv S34 database, and data on mergers and acquisitions come from Refinitiv SDC. Trademark information is gathered from the USPTO trademark case files, with trademark owners matched to Compustat firms via a fuzzy name-matching algorithm supplemented by manual verification. Additionally, we integrate various datasets, incorporating data on firm vertical integration, fluidity, and scope from the Hoberg-Phillips data library.

In the regression analysis, we exclude firms in heavily regulated industries such as finance (SIC code 6000-6999) and utilities (SIC code 4900-4999), although they are included in the descriptive analysis. We require firms to have traded common equity (CRSP share code 10 or 11) on major stock exchanges (CRSP exchange code 1, 2, 3 for NYSE, NASDAQ, and AMEX). Additionally, each firm-year must have positive asset and sales figures. Our final sample includes 158,219 firm-year observations. Table 2 reports the summary statistics of our firm-year sample. Approximately 7% of firms in our sample have filed at least one AI patent in a given year. On average, firms file 0.34 AI patents annually, which is significantly lower compared to the 4.67 non-AI patents filed each year. Additionally, other firm-level characteristics, such as *Ln(Assets)*, *Tobin's Q*, and *Leverage*, are also reported.

2.3 Descriptive Analysis

2.3.1 Distribution of AI patents

We illustrate the distribution of AI patents across various industries using the Fama-French 12 industry classification in Table 1. AI patents are widespread across all industries, yet the extent of AI technology filings varies significantly among them. The Business Equipment sector has the highest prevalence of AI-oriented firms, with one-third of firms in this category holding AI patents. This sector accounts for 75% of all AI patent filings, averaging 176 patents per firm. It is closely followed by Healthcare and Manufacturing, indicating that these sectors systematically adopt AI innovation to enhance productivity, efficiency, and competitive advantage.

A distinct concentration of AI activity is observed in certain sectors. In finance and retail, although only a small fraction of firms have applied for AI patents, these patents represent around a third of all patents filed within these sectors. This pattern suggests that a few trailblazing firms have adopted AI, while the majority have not. In contrast, industries such as Oil, Gas, and Coal Extraction and Products show minimal AI patent activity, indicating potential barriers to AI adoption due to regulatory and operational challenges.

Over time, we observe a gradual increase in the absolute number of AI patents from 1976 to 1993, followed by a substantial rise with advances in computer hardware (Panel A of Figure 1). As computational resources became more capable and accessible, they enabled more sophisticated AI developments, leading to an increase in patentable innovations. This period likely coincides with significant milestones in AI, such as improved algorithms, the availability of large datasets, and the emergence of machine learning as a dominant AI technique. Notably, the number of patents filed decreased in the last three years (2018-2020) due to delays in the patent approval process.[3] The share of AI patents out of all patents shows a similar pattern but seems to flatten after 2011, indicating a possible stabilization in the role of AI within the broader innovation landscape (Panel B of Figure 1).

AI technologies can be classified into different categories. Figure 2 shows the distribution of AI patents across various fields. Planning/Control is the most patented area within AI (28%), followed by Knowledge Processing (26%), AI Hardware (16%), and Computer Vision (13%). Examples of Planning/Control patents include robotics path planning, automated financial planning, and manufacturing process control. The other leading area, Knowledge Processing, covers natural language understanding, expert systems, and question-answering systems. It appears that firms' R&D efforts are concentrated on automating operations and assisting in decision-making in complex situations. The explosion of AI patents after 1993, shown in Figure 1, seems driven by the dramatic increase in patents filed in Planning/Control, Knowledge Processing, and Computer Vision, along with advancements in AI Hardware (Panel C of Figure 1).

We investigate the types of firms seeking AI patents in Figure 3, distinguishing between

[3]This is known as grant lag. As the dataset ends in 2020, we cannot see, for example, patents filed in 2019 but granted in 2022; thus, for empirical analysis, we limit our sample to include data up to 2016.

those filed by public firms (linked to public firms according to Kogan et al. (2017)) and private firms (identified by organizational names such as Ltd., LLC., etc., with US addresses). The allocation is nearly balanced between the two groups. Before 2010, US public firms accounted for a larger portion of AI patent filings compared to private firms. However, from 2010 onwards, private firms began to claim a larger share. This study focuses on patents filed by public firms due to data availability, but examining AI innovations from private firms remains a compelling area of research due to their growing share of AI patent filings in recent times. The sample includes a substantially higher number of private firms than public ones, resulting in a higher average number of patents per public firm, as they are generally larger.

2.3.2 The characteristics of AI developing firms

In this section, we analyze the characteristics of firms that file for AI patents. We consider a vector of variables potentially related to AI development, including firm size, value, capital intensity, R&D, ownership structures, and financing. Importantly, we control for the number of non-AI patents filed by the firm, ensuring that we do not merely capture overall patenting activities.

In Column (1) of Table 3, the dependent variable is an indicator assigned a value of one if a firm files at least one AI patent in a given year and zero otherwise. Additionally, we analyze the number of AI patents filed in that year. For the indicator variable, we use a linear probability model, and for the count of AI patents, we use Poisson regression. Both models are estimated with industry fixed effects to explore cross-sectional variations within industries and firm fixed effects to explore within-firm variations.

Our findings indicate that firms with larger assets, higher Tobin's Q, lower leverage, younger ages, higher profitability, and greater institutional ownership are more inclined to file AI patents. These results suggest that these firms are likely to be "superstar" firms that grow to a large size at younger ages. These firms typically exhibit lower levels of capital intensity, measured by property, plant, and equipment (PP&E) scaled by total assets.

Regarding financing, there is a negative correlation between equity issuance and AI patent filings, and a positive correlation between debt issuance and AI patent filings, suggesting that firms may finance these innovations through debt rather than equity. Additionally, these firms

are less inclined to pay dividends, invest more in R&D, and have higher capital expenditures.

In Table A.5, we examine the relationship between AI patent filings and various CEO characteristics, including age, tenure, education, and work experience. Our analysis reveals that younger, male CEOs, as well as those who are founders or inventors, are significantly more likely to file for AI patents. Additionally, CEOs with diverse work experience, reflecting higher general ability, and those with advanced educational qualifications such as MBAs and PhDs, show a stronger propensity for filings AI patents.

3 Empirical Results

3.1 Characteristics of AI Patent

In this section, we examine the characteristics of AI patents. We regress patent characteristics on AI patent indicator to capture the difference between AI and non-AI patents. By employing firm-by-(granted)year and technological subclass (IPC 4-digit)-(grant)year fixed effects, we compare the quality of AI patents to non-AI patents coming from the same firm and granted in the same year and in the same technological subclass. The results are presented in Table 4.

In Panel A, we investigate how firms harness existing knowledge to drive AI innovations and develop AI innovation strategies. Our analysis suggests that AI patents, as indicated in Column 1, cite a significantly higher number of prior patents, demonstrating that these patents are more deeply entrenched in existing knowledge. Notably, AI patents disproportionately cite other AI patents[4], and firms frequently reference their own AI patents. This trend indicates that AI patents are not primarily supplementary enhancements to existing non-AI technologies — such as integrating autonomous driving features into current car systems — but are instead focused on expanding and refining a firm's existing AI capabilities. Further examination of the distribution of AI patents' backward citations across technological classes, as shown in Column 2, indicates that AI patents tend to draw from a narrower spectrum of

[4]On average, over 50% of AI patent citations are directed towards other AI patents, with only 10% exclusively citing non-AI patents, even though AI patents account for just 10% of the entire sample.

technological classes, as reflected by their originality scores.[5] Since AI patents predominantly cite other AI patents, they tend not to incorporate knowledge from other fields, suggesting AI's position as a niche domain with limited reliance on cross-disciplinary insights. This specialization is further mirrored in firms' AI innovation strategies, where firms are more inclined to use AI patents to enhance existing capabilities — focusing more on exploitation rather than exploration, as noted in March (1991). This suggests that firms are leveraging AI primarily to build on and strengthen existing technologies, particularly within the realm of AI, rather than exploring new technological frontiers.

In Panel B, we analyze the knowledge spillover effects of AI patents, as well as their value and technological significance. Column 1 shows that AI patents are of higher quality than non-AI patents, as measured by the widely recognized indicator — the number of forward citations (Trajtenberg, 1990; Hall, Jaffe, and Trajtenberg, 2005; Harhoff, Scherer, and Vopel, 2003). This finding not only highlights the higher quality of AI patents but also suggests they generate more substantial knowledge spillovers, indicating greater technological importance. In Column 2, we observe that the knowledge spillover from AI patents spans a wider range of technological classes, as evidenced by higher generality scores.[6] It reflects the distribution of forward citations across various technological domains, supporting the idea that AI patents may function as general-purpose technologies, facilitating applications across multiple fields. Additionally, we find that, on average, over 85% of AI patent citations originate from firms other than those that developed them, further reinforcing their technological significance across the economy. This is further supported by the breakthrough innovation measure by Kelly et al. (2021), which assesses patent similarities.[7] As shown in Column 3, AI patents are approximately 10% more likely to be classified as breakthrough patents based on this metric.

However, an intriguing finding is that AI patents do not process higher market value as

[5]Originality is calculated as one minus the HHI of the technology classes cited by the focal patents. A higher originality score indicates that the patent draws from a diverse set of prior arts, suggesting greater originality and potentially higher value Trajtenberg, Henderson, and Jaffe (1997); Gompers, Lerner, and Scharfstein (2005). Conversely, a lower originality score may indicate reliance on a single field, signaling less innovation.

[6]Generality is calculated as one minus the HHI of the technology classes of future patents citing the focal patent.

[7]The breakthrough measure for a patent is q = Forward Similarity/Backward Similarity. A higher q indicates that the patent is more distinct from past innovations (novel) and more likely to guide future innovations (path-setting). We use the breakthrough patent data provided by Kelly et al. (2021), representing the top 10% q for 5-year forward/backward similarity.

measured by the value metric from Kogan et al. (2017). This metric primarily reflects the value to the developing firm, derived from stock market reactions to patent grant announcements. It suggests that AI patents do not confer significantly greater value to the developing firm compared to non-AI patents. This highlights the distinction between patent quality measures and private value, as all quality metrics, such as forward citations and breakthrough measure, assess the patent's impact on the broader economy rather than on the firm alone. Despite the considerable technological significance of AI technologies for the overall economy, the benefits realized by the developing firms may be relatively modest. We explore these dynamics in greater detail in subsequent sections.

In Panel C, we explore the sources of the technological significance of AI patents by drawing on key measures of technological novelty from the innovation literature (Verhoeven, Bakker, and Veugelers, 2016). The literature suggests that innovations can be considered novel in three primary ways: First, novelty in recombination occurs when an invention combines components and principles in a way that differs from previous technologies. This is captured by the indicator variable *Novelty: Recomb*, which equals one if the patent involves new IPC Group pair combinations, and zero otherwise. Second, an invention exhibits novel technological knowledge origins if it incorporates knowledge from previously untapped domains within its technological field, thereby unlocking new knowledge areas. This is measured by the indicator variable *Novelty: Knowledge Origins*, which also equals one if the patent involves new IPC Group pair combinations with its cited prior arts, and zero otherwise. Third, an invention can derive its novelty from basic science, which is measured by *Basic Science*, the number of non-patent literature (scientific) backward citations. Additional details on the construction of these variables can be found in Appendix A.1.

Our analysis suggests that AI patents do not exhibit novelty in recombination or serve as a source of new technological knowledge origins. However, the results suggest that the technological significance of AI may derive from its foundation in basic science. When combined with findings of higher forward citations and broader applicability, as indicated by generality measures, we argue that AI patents function as a bridge between basic science and applied science.

3.2 AI patents and firm growth

Innovations are the drivers of firm growth (Klette and Kortum, 2004; Akcigit and Kerr, 2018; Acemoglu, Akcigit, Alp, Bloom, and Kerr, 2018; Kogan et al., 2017). This section tests the firm growth effects of AI innovation and compares them to non-AI innovation. Following Kogan et al. (2017), we consider horizons (τ) of 1 to 5 years for the growth of five variables (profits, sales, capital, employment total factor productivity). The empirical model is

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \beta_0 + \beta_1 \theta_{i,t}^{AI} + \beta_2 \theta_{i,t}^{non-AI} + \delta X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t}, \quad (1)$$

where θ is the aggregated market value of AI/non-AI patents granted in year t by firm i scaled by total assets[8] i.e. $\theta = \frac{\sum \xi_{p,i,t}}{AT_{i,t}}$. ξ_p denotes market value of patent p. We also include a set of control variables, including log capital stock, log of employment, log total asset, and idiosyncratic volatility. All regression specifications use industry (SIC3)- and year-fixed effects. Our coefficient of interest is β_1, which captures the effect of firm AI innovation on growth and compare it with β_2, which capture the ffect of firm non-AI innovation. We normalize all right-hand variables to unit standard deviations for the ease of interpretation.

Panels A to D of Table 5 use firm growth proxies as dependent variables, measured by the growth rate of profits (Panel A), sales (Panel B), capital (Panel C), and employment (Panel D). The results suggest that future firm profits and sales are associated with the firm's AI innovation market value, although the magnitude of the coefficients is roughly half to one-third of those of non-AI patents' market value. For example, a standard deviation increase in the market value of AI (non-AI) patents is correlated with a 1% (3.0%) increase in a firm's profit growth over five years. We find similar patterns in a firm's sales growth, capital stock and employment. Panel E of Table 5 examines the relationship between AI innovation and firm productivity. We observe a very weak relationship over a one-year period, which does not persist over longer terms. Additionally, the size of the coefficient is fairly small compared to non-AI patents. For a unit increase in non-AI patent market value, a firm experiences a 1.6%

[8] As discussed in Kogan et al. (2017), larger firms tend to file for more patents, so the firm innovation index may inherently capture firm size. Normalizing by total assets allows for cross-firm comparisons independent of firm size. We also control for log capital stocks, log employment, and log total assets to further mitigate the effect of firm size.

to 1.7% increase in productivity over one to two years. This effect seems to fade away after the third year.

The evidence indicates that AI patents contribute less to firm growth than non-AI patents, despite their technological significance highlighted in our earlier patent-level analysis. This result is puzzling, as one would naturally expect that higher-quality patents would drive greater firm growth. This discrepancy again highlights the difference between the broader economic value created through knowledge spillovers and the direct benefits accruing to the inventing firm. It appears that firms may not fully capitalize on the value of these patents depending on how they are utilized. Instead, AI patents seem to act more as public goods, with firms capturing a smaller share of their total value compared to non-AI patents.

To explore why AI patents have a smaller impact on growth, we examine how these patents are used within the inventing firms. As shown in our earlier patent-level regressions, AI patents are predominantly employed to build on existing capabilities (more exploitative), particularly in AI-related areas, even though they have the potential to be applied across a broader range of fields by other firms. We hypothesize that the exploitative nature of AI patents may limit their impact on firm growth. In Table A.6, we find that exploitative patents generally have a smaller impact on growth compared to explorative patents, regardless of whether they are AI or non-AI patents. This finding is consistent with earlier studies, such as Colombelli, Krafft, and Quatraro (2013).

In Table 6, we repeat this analysis by focusing specifically on AI patents, dividing them into exploitative and explorative. The results show that, once again, exploitative AI patents contribute less to growth than explorative AI patents, except for profit growth. These findings support our hypothesis that the lower growth effects associated with AI patents, despite their higher technological significance, may be due to firms' innovation strategies that emphasize exploitation over exploration. However, exploitative use alone does not fully explain this phenomenon. Further research is needed to uncover the underlying dynamics. The key takeaway is that AI patents, despite their potential, do not contribute to firm growth as much as non-AI patents.

Concerns may arise that the lack of stronger growth results for AI compared to non-AI could be attributed to AI's lesser prevalence in earlier periods. It is plausible that AI could

significantly contribute to growth in more recent times following the AI boom. To address this, we conducted regression analyses for the period from 2000 to 2016, with the results reported in Appendix Table A.8. These findings are qualitatively similar, suggesting that the impact of AI on growth, when compared to non-AI, remains consistent across different time periods, even during the recent surge in AI's popularity.

3.3 AI, Corporate Finance Policies and Firm Outcomes

Our analysis thus far has primarily focused on characteristics of AI patents and how these patents are associated with various firm-level characteristics and firm growth. While these correlations provide valuable insights into overarching trends, it is important to acknowledge that the decisions to develop and patent AI inventions are endogenous. Consequently, these correlations do not automatically imply causation between AI patenting and firm outcomes. In this section, our goal is to investigate the causal impact of obtaining intellectual property rights for AI-related inventions on finance policies and firm outcomes.

To investigate the causal relationship between AI patents and firm-level outcomes, one would ideally assign AI patents to firms randomly and then measure the resulting outcomes. However, such an experiment is impractical in the real world. As a practical alternative, we employ a two-stage least squares (2SLS) methodology, as described in Farre-Mensa, Hegde, and Ljungqvist (2020), using examiner leniency as an instrumental variable to leverage the quasi-random nature of the US Patent and Trademark Office's (USPTO) review process for patent applications. This approach is predicated on the observation that patent applications are assigned to examiners in a quasi-random manner, with examiners varying in their leniency towards granting patents. Thus, a patent of similar quality may be approved by a more lenient examiner but rejected by a stricter one. The approval likelihood of a marginal patent, therefore, hinges on the examiner's leniency — a factor presumed to be independent of the patent's quality and the characteristics of the firm, due to the quasi-random assignment to examiners.

It is important to emphasize, however, that this methodology is not intended to instrument firm decisions on whether to "develop" or "patent" AI innovations, but rather to assess the impact of securing intellectual property rights for an invention, akin to the approach

used by Farre-Mensa, Hegde, and Ljungqvist (2020). Securing a patent grants exclusive rights to the invention, providing the patentee with monopoly power over it for a significant period. Conversely, following the enactment of the American Inventor Protection Act (AIPA) in November 1999 (effective November 2000) — which requires the publication of patent applications 18 months after filing with the USPTO — a rejected application exposes the technology to imitation, as most rejected applications become accessible to competitors.[9] Consequently, the value of the invention to the firm varies (plausibly exogenously due to the examination process) depending on whether property rights are secured or proprietary information is disclosed to competitors. These variations are independent of AI development efforts or patenting decisions, enabling us to capture the effects of increasing or decreasing the value of AI inventions and to analyze their outcomes. For this purpose, we focus on the sample period after AIPA took effect in November 2000. Therefore, our sample period for this analysis is from 2001 to 2016.

The construction of the firm-level leniency index is illustrated as follows. Suppose firm i filled multiple patent applications in year t. For each patent application p applied at time τ, we first measure the examiner leniency by calculating the approval rate of its assigned examiner j belonging to art unit a at application time τ:

$$Examiner\ Approval\ Rates_{pja\tau} = \frac{n_{granted_{ja\tau}}}{n_{reviewed_{ja\tau}}} \tag{2}$$

where the numerator and denominator refer to the number of patents granted and reviewed by examiner j before time τ, respectively. Then, we construct the firm-level leniency measure (i.e., $Leniency_{it}$) by summing the examiners' leniency ratios across all applications (i.e., both granted and rejected) for firm i in year t.

Importantly, it should be noted that the validity of the examiner's leniency serving as an instrument variable relies on the following two assumptions. Firstly, the assignment of the patent applications to examiners follows a quasi-random manner (i.e., Exclusion Condition). Secondly, given the quality of the innovation remains constant, the likelihood

[9] Less than 10% of rejected applications remain confidential. Firms can opt out of the 18-month publication rule by notifying the USPTO, but this is only possible if they do not seek protection outside the U.S., which is uncommon among companies and inventors pursuing broader protection.

of a particular patent being granted increases if its assigned examiner is more lenient (i.e., Relevance Condition). The quasi-random feature of USPTO's assignment rule is supported by the findings in previous literature (e.g., Lemley and Sampat (2012); Sampat and Williams (2019); Righi and Simcoe (2019)). Thus, it is unlikely that a randomly assigned examiner's past leniency could directly affect firm-level outcomes other than through the channel of affecting the success of the patent applications, suggesting that the exclusion condition for the validity of our instrument variable is plausibly satisfied. We then assess the "Relevance Condition" through the first stage regression of our 2SLS specification, which is shown as Equation 3 below.

$$\theta_{i,t}^{AI} = \beta_0 + \beta_1 \frac{Leniency_{it}^{AI}}{AT_{it}} + \beta_2 \frac{NApplications_{it}^{AI}}{AT_{it}} + \gamma X_{it} + \lambda_i + \lambda_t + \epsilon_{it} \tag{3}$$

where $\theta_{i,t}^{AI}$ represents the aggregate value of granted AI patents filed by firm i in year t scaled by total assets, and $Leniency_{it}^{AI}$ is the aggregated leniency measure for the examiners reviewing firm i's AI patent applications in year t. $NApplications_{it}^{AI}$ denotes the number of patent applications filed. These variables are scaled by total assets[10] and standardized to unit standard deviation to facilitate interpretation.

The primary control variable (included instrument) is the total number of AI patent applications, $\frac{NApplications_{it}^{AI}}{AT_{it}}$, which serves as a proxy for the firm's effort in developing and patenting AI technologies. Since we aggregate approval rates across applications for each firm-year, this metric is naturally correlated with the number of applications the firm submits. To ensure that the approval rates are not merely a reflection of application volume, we control for this variable. Consequently, any remaining variation in the number of granted patents should reflect approval driven by examiners' leniency, which is captured by the excluded instrument, $\frac{Leniency_{it}^{AI}}{AT_{it}}$. The control variables X_{it} include the logarithm of firm total assets and firm age. Additionally, firm and year fixed effects, λ_i and λ_t, are included to account for firm-specific time-invariant factors and overarching time trends in the granting of AI patents.

Table 7 presents the outcomes of the first-stage regression. Column 1 shows that the coefficient for the ratio of $\frac{Leniency_{it}^{AI}}{AT_{it}}$ is positive and statistically significant at the 1% level, indicating that examiner leniency in evaluating AI patent applications is a reliable predictor

[10] This approach helps mitigate the effect of firm size, as explained in section 3.2, and helps with normality for OLS regressions in 2SLS.

for the granting of AI patents. Coupled with F-statistics of over 300, this confirms that our instrumental variable meets the relevance criterion necessary for identification. Similarly, Column 2 of Table 7 shows a significant association between the leniency of examiners in reviewing non-AI patent applications and the number of non-AI patents granted. The negative coefficients observed on the included instrument and number of applications could be attributed to being overshadowed by the more predictive variable "leniency," yet these coefficients turn positive when the variables are included alone.

Then, we estimate the effects of AI patents on various firm-level outcomes through the second stage regression of the 2SLS

$$Y_{it} = \beta_0 + \beta_1 \widehat{\theta_{i,t}^{AI}} + \beta_2 \frac{No.Applications_{it}^{AI}}{AT_{it}} + \gamma X_{it} + \lambda_i + \lambda_t + \epsilon_{it} \tag{4}$$

where $\widehat{\theta_{i,t}^{AI}}$ is the predicted value of granted AI patents scaled by total assets obtained from Equation 3. In our setup, firms whose patent applications obviously fall short of or satisfy the criteria of being granted are "never takers" and "always takers", respectively, since their applications will be either rejected or approved regardless of the leniency of the examiners. Therefore, the Local Average Treatment Effects (LATE) we identified through 2SLS (i.e., β_1) only come from those compliant firms whose AI patent applications are subject to examiners' leniency (marginal patents). Next, we describe results using this instrumental variable approach.

3.3.1 Investment Policies

Table 8 presents the impact of AI and non-AI innovations on firms' investment decisions, as analyzed using Equation 4. We start by examining firms' direct investment decisions, with Columns 1 and 2 focusing on R&D expenditure and capital expenditure (CAPX) scaled by total assets as proxies. The results indicate that AI innovations do not significantly influence firms' direct investment decisions. In contrast, non-AI innovations appear to reduce firms' R&D expenditure while increasing capital expenditure. This suggests that after successful non-AI inventions, firms may reallocate resources toward capital investment to exploit and commercialize these innovations, potentially leading to a temporary reduction in R&D investments.

We then explore the impact of AI and non-AI innovations on firms' product market strategies, evaluating these strategies from multiple perspectives. Specifically, we analyze the degree of vertical integration using a firm-level index, "*VertInteg*", developed by Frésard, Hoberg, and Phillips (2019), where a higher score indicates more closely related product offerings within the supply chain. Additionally, we measure the breadth of a firm's product market presence using the "*d2vscope*" index from Hoberg and Phillips (2024), where a higher value reflects a wider range of product markets in which the firm operates.

Our findings show a decrease in vertical integration as the number of AI patents increases (Column 3), while the effect on firm scope is negative but statistically insignificant (Column 4). This suggests that firms focusing on AI may strategically choose to narrow their activities, prioritizing specialization or concentrating on specific areas of expertise rather than pursuing broad vertical integration across multiple product lines. These results align with our patent-level analysis, which indicates that AI innovations are often used to build on existing technologies rather than to expand into new fields. This challenges the assumption that AI, as a general-purpose technology, would naturally lead firms to broaden their product scope. It underscores the distinction between AI invention and AI application: while AI invention tends to focus on a narrower set of technological areas, firms that apply AI innovations might be more inclined to expand their operational scope.

Furthermore, we employ the number of new trademarks as a proxy for product innovation and commercialization, in line with the methodologies of Hsu, Li, Li, Teoh, and Tseng (2022) and Babina et al. (2024). The results in Column 5 reveal that, while non-AI patents are linked to an increase in trademarks acquired by firms, AI patents have a minimal impact on product innovation. This finding contrasts with Babina et al. (2024), which suggests that AI fosters firm growth through product innovation. The limited effect of AI innovation on trademarks may stem from AI's role as a feature-enhancing technology rather than a catalyst for entirely new product development.

Finally, we examine whether firms holding AI patents are more likely to become acquirers or targets in the M&A market. Column 7 shows that firms with AI patents are less likely to become acquisition targets, while there is little evidence indicating significant impacts of AI patents on a firm's decision to acquire (Column 6). One possible explanation is that

AI patents increase technological specialization, as found earlier, making these firms less attractive targets for other firms seeking technological complementarity (Bena and Li, 2014).

3.3.2 Firm Outcomes

In this section, we investigate the effect of AI patents on various firm outcomes using patent leniency as an instrumental variable. Table 9 presents the second-stage results for AI patents (Panel A) and non-AI patents (Panel B). In Column 1, we use total Q from Peters and Taylor (2017), which incorporates intangible capital into Q, to evaluate the effect on firm value. Since patents represent a form of intangible capital, it is crucial to properly account for this in calculating Q. Our findings indicate that both AI and non-AI patents enhance firm value, as measured by total Q, and they exhibit similar effects. The 2SLS estimator shows that a one standard deviation increase in the value of granted AI patents relative to assets, due to examiner leniency, leads to a rise in Q by 0.310. This increase corresponds to approximately 16% of the unconditional sample mean (1.98).

For firm profitability (Column 2), measured using operating income after depreciation scaled by total assets, we observe that while non-AI patents enhance profitability, AI patents do not have a similar effect. This finding is consistent with the firm growth regressions in section 3.2, where non-AI patents are associated with higher profit growth compared to AI patents.

Lastly, Column 3 examines the influence of both AI and non-AI patents on firm risk, measured by stock return volatility. The results suggest that patents, whether AI or non-AI, are associated with increased firm risk, which is expected given that innovation inherently involves risk. However, the effect of AI patents on firm risk is about half that of non-AI patents. This may be driven by the fact that AI patents tend to be more exploitative, and therefore involve less risk.

3.3.3 Financing Policies

We also investigate how AI patents influence firms' financing decisions, considering that patents can act as signals to investors or serve as collateral (Hochberg, Serrano, and Ziedonis, 2018), thus potentially affecting financing behaviors. Table A.9 presents the results of

the 2SLS analysis on the effects of AI patents (Panel A) and non-AI patents (Panel B) on various financing outcomes, including equity issuance, debt issuance, dividends, and share repurchases. Our findings indicate that AI patents do not significantly impact these financing decisions.

3.4 Knowledge Accumulation, Technological Spillover

Research and development (R&D) spillovers have long been a central topic in the literatures on growth, productivity, and industrial organization. Building on the stronger knowledge spillover effects of AI patents identified in section 3.1, we delve deeper into how AI influences follow-on innovations, both within the inventing firm and across other firms. This exploration is particularly relevant to understanding aggregate economic outcomes and total social welfare.

We start by examining follow-on innovation within the inventing firm, focusing on the relationship between AI and non-AI patents and the firm's future patenting activities. To do this, we estimate the following firm-level regression:

$$Pat_{i,t+1} = \exp(\beta_1 \ln(1 + Pat_{i,t-10,t}) + \beta_2 \ln(Spilltech_{i,t}) + \delta X_t + \alpha_i + \delta_t + \epsilon_{t+1}) \tag{5}$$

Here, $Pat_{i,t+1}$ represents the number of patents filed at $t+1$, which serves as our measure of future innovation.[11] This model allows us to compare the impact of AI and non-AI patents on subsequent innovation. Our approach mirrors the patent equation used in Bloom, Schankerman, and Van Reenen (2013), but with key modifications: we distinguish between AI and non-AI patent stocks and spillovers, focusing on patent stock rather than the R&D stock G_{it} used in their study. Specifically, $Pat_{i,t-10,t}$ captures the number of AI and non-AI patents filed by firm i over the past 10 years[12].

To calculate "Spilltech," which measures technological spillovers from other firms $j \in J$

[11] We also test with citation-weighted patent counts, yielding similar results.

[12] The results are not sensitive to the choices of number of years to accumulate patent stock.

to firm i, we follow the methodology of Bloom, Schankerman, and Van Reenen (2013):

$$Spilltech_{i,t} = \sum_{j \neq i} Tech_{ij} G_{jt} \tag{6}$$

$Tech_{ij}$ represents the technological similarity between firms i and j, determined by patent classifications. While Bloom, Schankerman, and Van Reenen (2013) employed the legacy US patent class (USPC) system, we use the more modern Cooperative Patent Classification (CPC) system. To calculate technological similarity, we use CPC 3-digit technology classes. In Bloom, Schankerman, and Van Reenen (2013), all patents filed by firm i over the entire sample period were combined to form a vector, and the uncentered correlation between these vectors determined the similarity between firms.

$$Tech_{ij} = \frac{(T_i T_j')}{\sqrt{(T_i T_i')(T_j T_j')}} \tag{7}$$

We use a rolling window of the past 10 years ($t-10$ to $t-1$) to form the vector, which allows us to capture the dynamic nature of a firm's innovation progress. Again, we substitute patent stock for G_{jt} in place of R&D stock. We control for the natural log of total assets, R&D expenses scaled by assets, and includes firm and year fixed effects.

The results, reported in Table 10, show that the accumulation of AI patents has a smaller effect on future overall patenting (Columns 1 to 3) where we regress all patents filed at $t+1$ on the stock of AI and non-AI patents, with the impact being most evident in future AI development (Columns 4 to 6). This finding aligns with our earlier results, which suggest that AI development primarily builds on existing AI technologies.

Regarding the technological spillovers measured by "Spilltech" — capturing the effects of technological spillovers from other firms on a focal firm's future innovation — we find that spillovers from both AI and non-AI patents exert similar influence when analyzed independently, regardless of whether the resulting innovation is AI-related or not (Columns 1, 2, 4, 5, 7, and 8). However, when both AI and non-AI spillovers are included in the same regression, AI spillovers emerge as the dominant force. This finding supports our earlier results, which indicate that AI generates more substantial knowledge spillovers, as evidenced

by higher forward citation rates and broader applicability across various technological fields.

This result highlights the significant positive externalities of AI patents: although they may be narrowly focused within the inventing firms, they deliver considerable benefits to other firms. This sharply contrasts with the pattern of knowledge accumulation within the focal firm, where AI knowledge primarily flows from AI to AI, with limited crossover to non-AI technologies. This reinforces our view that while firms develop AI to leverage existing AI capabilities, AI innovations also act as public goods, producing extensive knowledge spillovers that drive further innovation in both AI and non-AI domains across the industry.

In further analysis, we categorize firms into AI-experienced and AI-inexperienced groups based on whether they have filed at least one AI patent in the past 10 years (i.e., AI patent stock > 0) or not. The results, presented in Table 10 Panel B, suggest that technological spillovers are particularly potent for AI-experienced firms (Columns 1-3), suggesting that the findings in Panel A are largely driven by firms with prior AI innovation experience. Conversely, AI-inexperienced firms benefit from spillovers from both AI and non-AI patents of other firms (Columns 1, 2), though the effects are generally weaker than those observed in AI-experienced firms, and there is no clear dominance of one type of spillover over the other (Column 3). This indicates that while AI spillovers contribute to the development of both AI and non-AI patents, their impact is especially significant for firms that have already engaged in AI innovation.

3.5 Social Returns of AI Innovation

Given the substantial knowledge spillovers of AI innovation. We explore the social returns of AI patents by drawing from the methodology of Jones and Summers (2021) and closely following the steps outlined by Lerner et al. (2024). We calculate the average social return on AI innovations using the following formula:

$$\rho = \frac{g/r}{x/y}, \tag{8}$$

where g represents the growth rate in total factor productivity (TFP)[13] driven by AI

[13]We use the utilization-adjusted TFP from Basu, Fernald, and Kimball (2006). Available at https://www.frbsf.org/research-and-insights/data-and-indicators/total-factor-productivity-tfp.

innovation, r is the discount rate, x denotes the R&D investment in AI innovation, and y represents real GDP. The ratio g/r captures the present value of productivity gains attributable to AI innovation (the "benefit"), while x/y reflects the proportion of GDP allocated to AI innovation investment (the "cost").

To quantify the "benefits" derived from AI innovation, we estimate TFP by comparing AI innovation to overall innovation using the following ratio:

$$\frac{\text{AI innovation}}{\text{total innovation}} = \frac{\text{sum of weighted citations for granted AI patents}}{\text{sum of weighted citations for all granted patents}}. \tag{9}$$

We then determine the "cost" of AI innovation by aggregating the R&D expenditures of firms engaged in AI innovation, as follows:

$$\text{cost} = \sum_i \text{R\&D of firm}_i \times \frac{\text{\# of AI patents applied for by firm}_i}{\text{\# of total patents applied for by firm}_i}, \tag{10}$$

We condense these elements into our benchmark measure for the social returns of AI innovation:

$$\rho_t = \frac{g_{t+1}/r}{x_t/y_t}, \tag{11}$$

where $g_t = \text{TFP growth}_t \times \text{AI innovation share of total innovation}_t$; $r = 5\%$, a constant measure based on Jones and Summers (2021); $x_t =$ total R&D expenditure on AI innovation at time t, and $y_t =$ adjusted real GDP at time t.

For the social and private return analyses, we focused on firms that had at least one patent, were publicly traded in the U.S., and had a minimum of one year of non-missing or non-zero R&D expenditure data in Compustat.

Figure 4 presents the social return ρ of AI and non-AI innovation over time, based on our benchmark measure of innovation's social returns as detailed in Equation 11. On average, \$1 invested in R&D for AI innovation is estimated to have yielded \$15 in social returns between 1985 and 2017, compared to \$12 for non-AI — a 25% higher value. Between 1995 and 2005, the gap between AI and non-AI was at its peak. The negative returns in 2008 can be attributed to the Global Financial Crisis (GFC). Interestingly, the gap between AI and non-AI appears to diminish after the GFC, although AI consistently remains higher. It would be intriguing to

observe the pattern after the rise of AI post-2020, but our data is limited to 2020. Only before 2019 or earlier, meaningful variations may be observed due to truncation caused by delays in patent grants.

3.6 Industry Outcomes

Given these dynamics of AI innovation observed at the firm level, it becomes essential to examine the aggregated outcomes at the industry level. One might expect that winner-takes-most effects could lead to increased concentration (Babina et al., 2024), while alternatively, knowledge spillovers might benefit other firms, fostering their growth and thus reducing concentration. This distinction is crucial between AI-inventing and AI-using firms, as AI-inventing firms generate positive knowledge spillovers, rather than solely business-stealing effects. In the framework of Bloom, Schankerman, and Van Reenen (2013), both positive and negative technology spillovers arise from R&D. However, it remains uncertain whether AI innovation will produce sufficient knowledge spillovers to outweigh the business-stealing effects. Our focus is on comparing these effects with non-AI innovation. Given that AI is more of a general-purpose technology, it is likely to spill over to firms beyond those directly involved in AI development. To explore this, we estimate the following industry-level regression:

$$Y_{I,t+\tau} = \beta_0 + \beta_1 \frac{\text{AI Pat.}_{I,t}}{\text{Non-AI Pat.}_{I,t}} + \delta X_{I,t} + \alpha_I + \delta_t + \epsilon_{I,t+\tau} \tag{12}$$

where $Y_{I,t+\tau}$ represents industry-level outcomes such as sales, employment, and concentration. The key variable of interest is the ratio of AI patents to non-AI patents, capturing the proportion of AI patents within the industry's total patenting activity. Control variables, denoted by $X_{I,t}$, include the natural log of sales, employment, and the total number of patents. Given our focus on industry-level concentration, Hoberg and Phillips (2024) argues that Compustat Segment data is inadequate for this purpose.[14] Consequently, we adopt the methodology of Hoberg and Phillips (2024), utilizing text-based industry classifications and text loadings to

[14] Firms often aggregate their sales into a single industry rather than accurately reporting them across distinct segments. By correcting this using a text-based scope measure, they show that the concentration levels in U.S. industries have not been increasing over time as previously documented.

disaggregate firm sales into industry-specific concentration measures.[15] We apply the same approach to aggregate industry employment. Industry fixed effects (α_I) and year fixed effects (δ_t) are included to account for unobserved industry-specific and time-specific factors. Due to availability of the scope data, our sample period for this analysis is 1988 to 2016. The results are presented in Table 11.

In Panels A and B, we find that AI patents are associated with stronger future industry growth compared to non-AI patents. A 10% increase in the AI/All patents ratio at time t correlates with a 2% and 3.2% increase in industry sales and industry employment, respectively, over the next five years. This result supports the idea that AI technologies enhance features, drive customer demand, and generate positive knowledge spillovers, which appear to outweigh the disruptive effects on other firms, thereby contributing to overall industry growth.

In Panel C, we assess industry concentration using the Herfindahl-Hirschman Index (HHI) based on industry sales and find that AI contributes to heightened industry concentration, reflecting a winner-takes-most dynamic, as observed by Babina et al. (2024). To explore spillover effects beyond AI firms, we calculate the proportion of AI patents relative to total patents filed during the period $t-10$ to $t-1$ and use this measure as a loading factor to segregate firm sales into AI-related and non-AI-related. We then estimate industry HHI separately for AI-related and non-AI-related sales. we find a interesting patterns: within AI, concentration decreases as the ratio of AI patents increases (Panel D), aligning with our "Spilltech" analysis, whereas within non-AI, concentration rises (Panel E). This indicates that spillovers predominantly benefit AI-inventing firms, offsetting disruptive impacts, while the winner-takes-most dynamics in non-AI firms may be driven by their adoption of AI technologies developed by AI-inventing firms.

4 Conclusion

Our analysis of comprehensive AI patent data indicates that AI patents are not only of high quality but are also more likely to represent breakthrough innovations that generate

[15] In Table A.11, we follow Babina et al. (2024) and apply NAICS classifications for all Compustat firms to measure industry concentration. The results are qualitatively similar but weaker, likely due to over-bucketing issues and potential misclassifications noted by Hoberg and Phillips (2024).

significant knowledge spillovers. This technological significance appears to stem from the integration of basic science. Despite this, AI development tends to initially focus on building upon and leveraging firms' existing technologies, particularly their current AI capabilities. Notably, firms engaged in AI development do not experience significant increases in growth or profitability and seem to capture only a small fraction of the total value created by AI innovations. Consequently, AI patents act more like public goods, spurring further innovation across a broader range of technological fields, both within and beyond AI. This finding carries important innovation policy implications. The lower profitability associated with AI development could discourage firm investment in AI, which would be detrimental to social welfare, particularly given the substantial technological benefits and spillovers that AI innovations provide.

While the net effect of AI development on industry concentration is positive, we observe that it decreases the concentration of AI-inventing firms, likely because the knowledge spillover effects outweigh the business-stealing effects. In contrast, the concentration among non-AI-inventing firms increases, likely driven by their adoption of AI from AI-inventing firms. We also observe higher social returns from AI innovation per dollar invested in R&D, further highlighting its social value.

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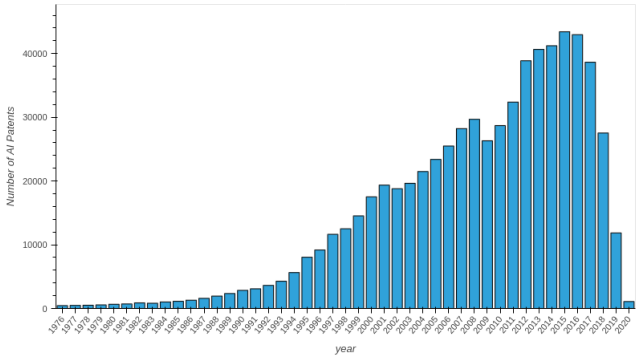
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5 Tables and Figures

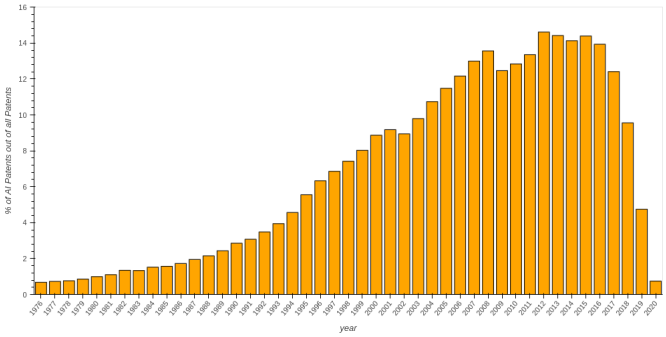
Figure 1: AI Patents by Year

This figure illustrates the distribution of AI patents from 1976 to 2020. Panels A to C plot the number of AI patents, the percentage of AI patents, and the number of AI patents by field, respectively.

Panel A - Number of AI patents



Panel B - Percentage of AI patents



Panel C - AI patents by Field

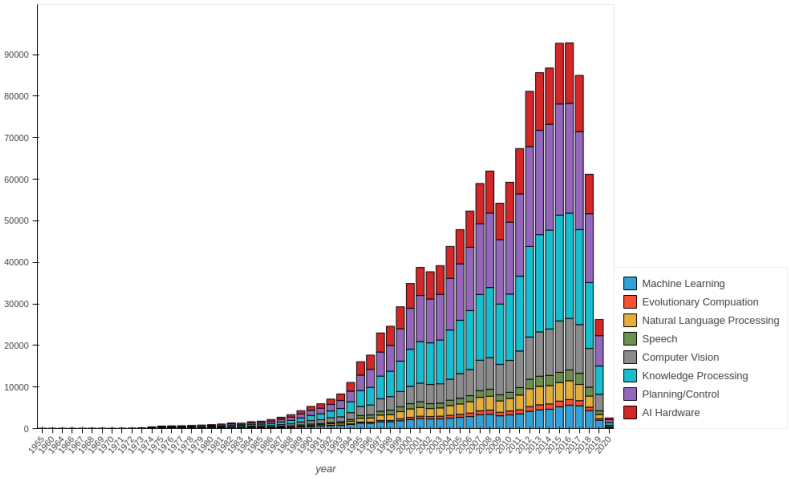


Figure 2: AI Patents by Fields

This figure plots AI patents by field from 1976 to 2020.

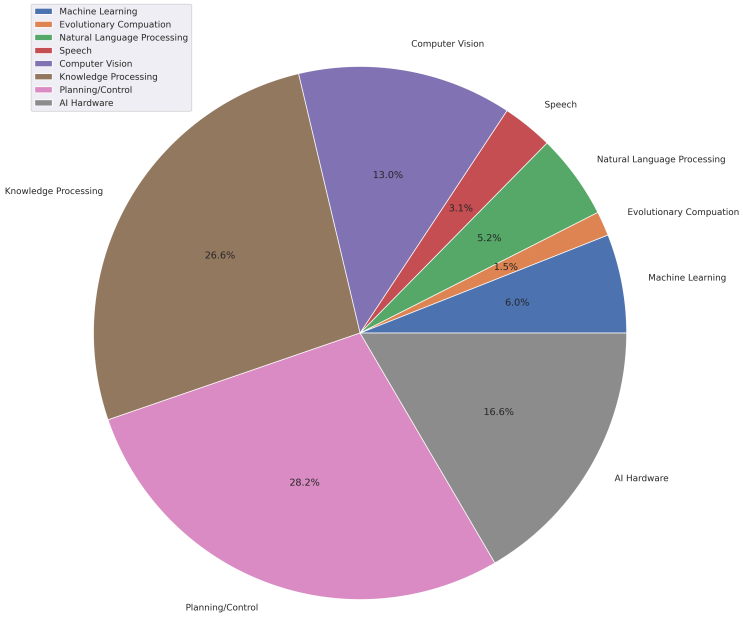


Figure 3: AI Patents by Firm Type

This figure plots AI patents from US Public firm or from Private firm/Foreign firm from 1976 to 2020.

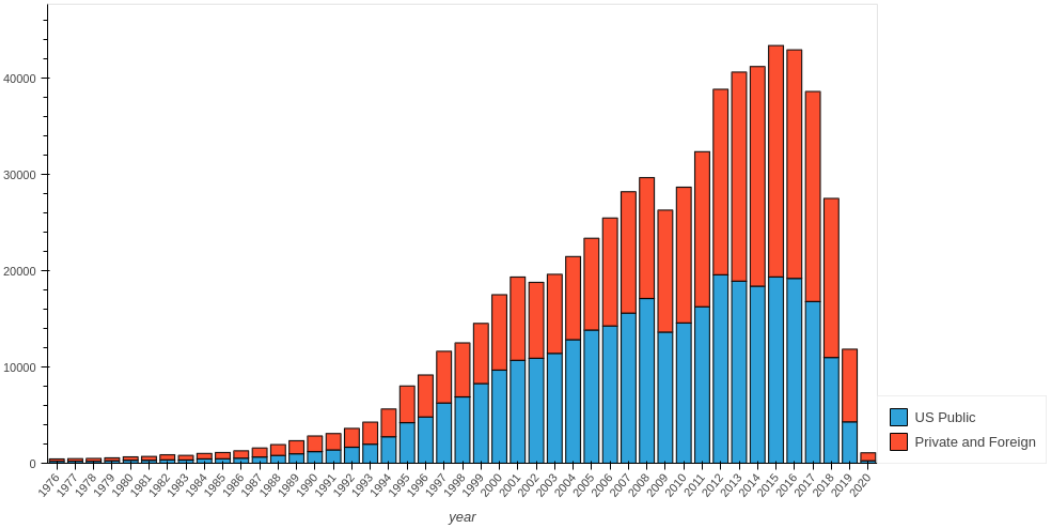


Figure 4: Social Returns to AI innovation

This figure presents the returns to AI innovation, comparing social returns from AI versus non-AI innovation over time using measures from Jones and Summers (2021) and the methodology from Lerner et al. (2024). The social return is calculated as:

$$\rho_t = \frac{g_{t+1}/r}{x_t/y_t}$$

Here, the ratio of the benefit g/r is determined using TFP growth weighted by the citations of granted patents. The discount rate r is exogenously set at 5%. The cost x/y is measured as the total R&D expenditure, weighted by the counts of filed patents and scaled by real adjusted GDP.

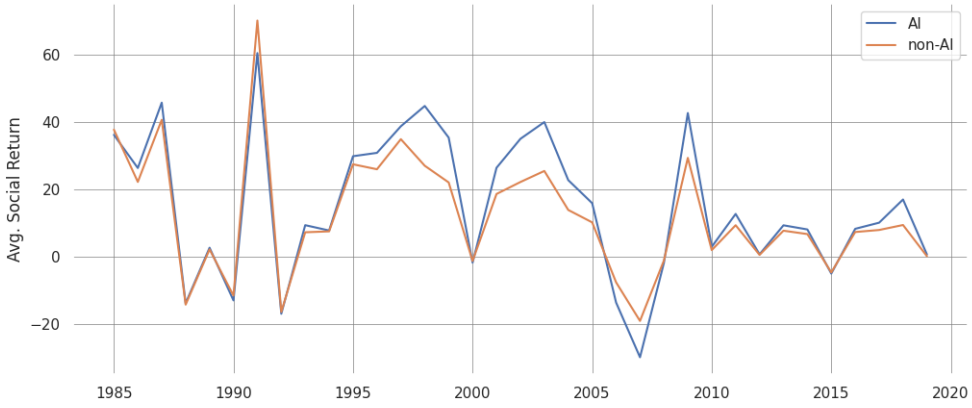


Table 1: Industry Distribution

The table provides AI patent distribution across the Fama French 12 industries from 1976 to 2020, focusing on firms with common equities, listed on major exchanges, and having positive asset values. We present total number of firms in each industry (*N firms*), the number of firms with at least one AI patent (*N AI firms*), the percentage of firms with AI patents in each industry (*% Has AI*), the total AI patents (*N AI Patents*), the number patents in the industry (*N patents*), and the percentage of AI patents relative to all patents (*% of All Pat.*).

Industry	N Firms	N AI Firms	% Has AI	N AI Patents	N Patents	% of All Pat.
Business Equipment	3,747	1,145	30.4	201,875	911,386	22
Consumer Durables	509	87	17.0	4,989	159,121	3
Healthcare, Medical Equipment, and Drugs	2,386	358	14.9	5,815	195,317	3
Chemicals and Allied Products	389	58	14.6	782	176,186	0
Manufacturing	1,997	277	13.6	10,964	378,118	3
Telephone and Television Transmission	598	72	11.0	13,333	113,858	12
Utilities	300	28	9.0	87	2,005	4
Other	2,999	170	5.6	9,412	128,742	7
Consumer Nondurables	1,130	58	5.1	532	36,117	1
Oil, Gas, and Coal Extraction and Products	955	43	4.6	2,266	134,756	2
Finance	3,483	118	3.3	9,042	33,315	27
Wholesale, Retail, and Some Services	2,174	64	2.9	8,842	26,234	34

Table 2: Summary Statistics for Firm-Year Sample

This table presents summary statistics for firm-year observations over the sample period from 1976 to 2020. I(AI) is an indicator variable that equals 1 if the firm filed at least one AI patent in a given year. N(AI) and N(non-AI) represent the number of AI and non-AI patents filed, respectively. Detailed definitions of these variables are provided in Appendix Table A.1.

	N	Mean	25%	50%	75%	std. dev
I(AI)	158,219	0.07	0.00	0.00	0.00	0.26
N(AI)	158,219	0.20	0.00	0.00	0.00	0.98
N(Non-AI)	158,219	2.32	0.00	0.00	1.00	9.24
Ln(Assets)	158,219	4.80	3.23	4.66	6.26	2.17
Tobin's Q	156,284	1.98	1.04	1.40	2.17	1.71
Leverage	158,210	0.71	0.03	0.34	0.88	2.12
PPE/AT	158,026	0.28	0.10	0.22	0.41	0.22
ROA	158,216	-0.05	-0.05	0.03	0.08	0.27
XRD/AT	158,219	0.05	0.00	0.00	0.05	0.10
Missing XRD	158,219	0.41	0.00	0.00	1.00	0.49
XAD/AT	158,219	0.01	0.00	0.00	0.01	0.04
CAPX/AT	158,219	0.07	0.02	0.04	0.08	0.07
Dividends/AT	157,983	0.01	0.00	0.00	0.01	0.02
Inst. Own	158,219	0.31	0.03	0.22	0.54	0.30
Equity Issue	158,219	0.11	0.00	0.00	0.00	0.31
Debt Issue	158,219	0.09	0.00	0.00	0.00	0.28
Firm Age	158,219	13.65	4.00	9.00	18.00	14.59
HHI (SIC)	158,219	0.27	0.13	0.22	0.35	0.20
Sale Growth	141,666	0.11	-0.03	0.09	0.22	0.49
Asset Growth	141,666	0.08	-0.04	0.06	0.19	0.34
OI/AT	158,204	-0.00	-0.02	0.07	0.13	0.52
VOL	156,161	0.00	0.00	0.00	0.00	0.01
New TM	158,219	0.43	0.00	0.00	1.00	0.50
Acquirer	158,219	0.03	0.00	0.00	0.00	0.16
Target	158,219	0.03	0.00	0.00	0.00	0.16
Vert. Integ.	105,719	0.01	0.00	0.01	0.01	0.01
Repurchase/AT	60,331	1.00	1.00	1.00	1.00	0.00

Table 3: Firm Level Determinants

This table presents the firm level determinants of AI patent filings. The sample period spans from 1976 to 2016. The dependent variable in Columns 1 and 2 is the indicator variable that is equal to one if the firm has filed at least one AI patent in a given year, and zero otherwise. The dependent variable in Columns 3 to 4 is the number of AI patents filed in the given year. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. All potentially unbounded variables are winsorised at 1% level. Detailed variable definitions are provided in Appendix Table A.1.

	I(AI)		N(AI)	
	(1)	(2)	(3)	(4)
Ln(Assets)	0.017***	0.018***	0.504***	0.299***
	(14.98)	(10.16)	(22.45)	(10.42)
Tobin's Q	0.009***	0.005***	0.083***	0.049***
	(11.59)	(7.14)	(6.91)	(5.55)
Leverage	-0.001***	-0.000	-0.015**	-0.004
	(-3.24)	(-0.97)	(-2.10)	(-0.87)
PPE/AT	-0.050***	-0.026***	-0.602**	0.510**
	(-8.28)	(-3.28)	(-2.10)	(2.06)
ROA	0.021***	-0.005	0.403***	0.051
	(5.38)	(-1.62)	(3.88)	(0.76)
XRD/AT	0.166***	0.017	4.353***	1.009***
	(8.60)	(0.94)	(13.77)	(3.41)
Missing XRD	-0.010***	0.004	-1.016***	-0.045
	(-4.30)	(1.51)	(-8.06)	(-0.45)
XAD/AT	-0.044	-0.062*	0.464	-1.629*
	(-1.36)	(-1.78)	(0.51)	(-1.87)
CAPX/AT	0.024**	0.010	1.348***	0.739*
	(2.50)	(1.15)	(2.74)	(1.85)
Dividends/AT	-0.337***	-0.019	-4.318***	-1.514**
	(-8.14)	(-0.50)	(-3.49)	(-2.05)
Inst. Own	0.032***	0.009	0.691***	0.127
	(4.67)	(1.34)	(5.91)	(1.51)
Equity Issue	-0.016***	-0.002	-0.088**	-0.009
	(-7.06)	(-0.90)	(-2.07)	(-0.30)
Debt Issue	0.004	0.006**	-0.023	-0.007
	(1.22)	(2.37)	(-0.73)	(-0.34)
Firm Age	-0.001***	-0.005***	-0.002	-0.004
	(-4.07)	(-2.75)	(-0.95)	(-0.45)
HHI (SIC)	0.003	0.007	0.244	0.011
	(0.35)	(0.64)	(1.44)	(0.06)
Non-AI Patents	0.012***	0.009***	0.020***	0.018***
	(46.91)	(21.05)	(12.25)	(11.28)
SIC4 FE	✓		✓	
Year FE	✓	✓	✓	✓
Firm FE		✓		✓
Obs.	155,920	154,576	133,617	36,587
R^2	0.34	0.57		

Table 4: Patent Characteristics

The table reports the differences in patent characteristics for AI and non-AI. Data is at patent level. *AI* is an indicator variable equal to one if the patent is a AI patent and zero otherwise. *Back. Cites.* is the number of U.S. patents cited by the patent; *Originality* is the 1-HHI index of IPC4 classes of the backward citations; *Exploitative* is an indicator variable equal to 1 if more than 90% of backward citations are to patents by the same firm or patents the firm has cited before; *Explorative* is an indicator variable equal to 1 if less than 10% of backward citations are to patents by the same firm or patents the firm has cited before; *Forw. Cites* is the number of U.S. patents citing the patent; *Generality* is the 1-HHI index of IPC4 classes of the forward citations; ξ is the market value of the patent as in Kogan et al. (2017). *BK10* is the innovation breakthrough measure as in Kelly et al. (2021). *Novelty: Recomb* is an indicator variable equal to 1 if the patent has new IPC Group pair(s) combinations and zero otherwise. An invention is identified as having novelty in recombination if the combination of components and principles applied to serve its purpose are different from those in previous technologies; *Novelty: Know. Origins* is an indicator variable equal to 1 if the patent has new IPC Group pair(s) combinations with its cited prior arts and zero otherwise. An invention is identified as having novel technological knowledge origins if it draws technological knowledge from domains that were previously not used in the technological domain of the invention; *Science* is the number of non-patent literature (scientific) backward citations. Detailed variable definitions are provided in Appendix Table A.1. Firm by granted year and IPC4 class by granted year fixed effects are included in all specifications. T-statistics adjusted for clustered standard errors at the main IPC4 class level are reported in parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. All potentially unbounded variables are winsorised at 1% level. The sample period is 1976 to 2016.

Panel A - Source of AI Knowledge and AI Innovation Strategy

	Back. Cites	Originality	Exploitative	Explorative
	(1)	(2)	(3)	(4)
AI	0.120***	-0.015***	0.012**	-0.017***
	(3.85)	(-4.70)	(2.44)	(-4.04)
Model	Poisson	OLS	LPM	LPM
IPC4 × Year FE	✓	✓	✓	✓
Firm × Year FE	✓	✓	✓	✓
Obs.	1,965,182	1,881,323	1,965,274	1,965,274
R^2		0.14	0.15	0.20

Panel B - Knowledge Spillovers, Values and Technological Importance of AI

	Forw. Cites	Generality	BK10	Ln(ξ)
	(1)	(2)	(3)	(4)
AI	0.422***	0.024***	0.095***	0.001
	(28.91)	(6.58)	(14.42)	(1.43)
Model	Poisson	OLS	LPM	OLS
IPC4 × Year FE	✓	✓	✓	✓
Firm × Year FE	✓	✓	✓	✓
Obs.	1,964,686	1,623,945	1,964,956	1,965,274
R^2		0.22	0.33	0.92

Panel C - Technological Novelty of AI

	Novelty Recomb	Novelty Know. Origins	Basic Science
	(1)	(2)	(3)
AI	0.001	-0.001	0.446***
	(1.12)	(-0.64)	(18.43)
Model	LPM	LPM	Poisson
IPC4 × Year FE	✓	✓	✓
Firm × Year FE	✓	✓	✓
Obs.	1,965,226	1,965,226	1,886,140
R^2	0.14	0.19	

Table 5: Firm Growth

The table presents the relation between AI and non-AI patents and firm-level outcomes. β_1 and β_2 from estimations of the following model are reported:

$$ln(Y_{i,t+\tau}) - ln(Y_{i,t}) = \beta_0 + \beta_1 \theta_{i,t}^{AI} + \beta_2 \theta_{i,t}^{non-AI} + \delta X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm outcomes, $\theta_{i,t}^{AI/non-AI}$ is the aggregated market value of AI/non-AI patents granted in year t by firm i scaled by total assets, $X_{i,t}$ is a vector of control variables including log capital stock, log of employment, log total asset, and idiosyncratic volatility, and $\tau \in 1-5$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. The sample period is 1976 to 2016. Panel A presents results for firm gross profits (sales minus cost of good sold), Panel B for firm sales, Panel C for firm capital stock (property, plants, and equipment), Panel D for firm employment, and Panel E for firm total factor productivity (TFP). effects. Standard errors are clustered at the firm level. T-statistics adjusted for clustered standard errors are reported in parentheses. All unbounded variables are winsorized at 1% level. ***, **, * indicates significance level at 1%, 5% and 10%. Detailed variable definitions are provided in Appendix Table A.1.

	t+1	t+2	t+3	t+4	t+5
			Panel A. Profits		
AI	0.004*	0.010***	0.011***	0.011***	0.010**
	(1.86)	(3.04)	(3.01)	(2.76)	(2.23)
Non-AI Pat.	0.012***	0.020***	0.025***	0.028***	0.030***
	(6.32)	(5.82)	(4.45)	(4.41)	(4.34)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel B. Sales		
AI	0.005**	0.008***	0.010***	0.012***	0.012***
	(2.47)	(2.74)	(3.08)	(3.55)	(3.30)
Non-AI Pat.	0.015***	0.024***	0.028***	0.029***	0.030***
	(6.97)	(6.94)	(6.28)	(5.39)	(4.54)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel C. Capital		
AI	0.010***	0.014***	0.013***	0.013***	0.015***
	(3.21)	(2.84)	(3.25)	(3.18)	(3.39)
Non-AI Pat.	0.010***	0.021***	0.028***	0.032***	0.033***
	(6.84)	(7.81)	(8.56)	(7.97)	(6.94)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel D. Employment		
AI	0.004**	0.006**	0.008***	0.010***	0.011***
	(2.43)	(2.42)	(3.19)	(3.39)	(3.68)
Non-AI Pat.	0.010***	0.017***	0.019***	0.019***	0.019***
	(7.77)	(7.61)	(7.04)	(6.13)	(5.07)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel E. Total Factor Productivity		
AI	0.003**	0.003*	0.005	0.006*	0.005
	(2.10)	(1.85)	(1.55)	(1.75)	(1.32)
Non-AI Pat.	0.015***	0.016***	0.006	0.005	0.008
	(6.03)	(7.10)	(0.84)	(1.05)	(1.58)
Obs.	106,627	96,654	88,705	81,710	74,058

Table 6: Firm Growth - AI Explorative vs. Exploitative AI

The table repeats the analysis of Table 5, but disaggregate $\theta_{i,t}^{AI}$, which is the aggregated market value of AI patents granted in year t by firm i scaled by total assets, into Exploitative and Explorative. Detailed variable definitions are provided in Appendix Table A.1.

	t+1	t+2	t+3	t+4	t+5
			Panel A. Profits		
AI (Exploitative)	0.007***	0.009**	0.011**	0.011***	0.010**
	(2.64)	(2.47)	(2.52)	(2.58)	(2.04)
AI (Explorative)	0.003	0.009***	0.009***	0.010***	0.010***
	(1.28)	(2.95)	(2.85)	(3.42)	(3.18)
Non-AI	0.013***	0.021***	0.026***	0.028***	0.031***
	(6.81)	(5.80)	(4.22)	(4.17)	(4.13)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel B. Sales		
AI (Exploitative)	0.001	0.002	0.004	0.005	0.005
	(0.74)	(0.72)	(1.01)	(1.29)	(0.89)
AI (Explorative)	0.006***	0.010***	0.010***	0.012***	0.012***
	(3.45)	(3.45)	(3.64)	(4.30)	(4.20)
Non-AI	0.015***	0.025***	0.030***	0.031***	0.033***
	(7.06)	(6.89)	(6.43)	(5.72)	(5.14)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel C. Capital		
AI (Exploitative)	-0.000	0.001	0.003	0.005	0.006*
	(-0.33)	(0.54)	(1.34)	(1.55)	(1.65)
AI (Explorative)	0.014***	0.018***	0.015***	0.015***	0.016***
	(4.22)	(4.10)	(5.92)	(5.40)	(4.86)
Non-AI	0.010***	0.021***	0.029***	0.032***	0.035***
	(7.03)	(7.73)	(8.09)	(7.67)	(7.22)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel D. Employment		
AI (Exploitative)	0.001	0.003	0.006**	0.007**	0.008**
	(0.73)	(1.59)	(2.25)	(2.31)	(2.26)
AI (Explorative)	0.005***	0.006***	0.007***	0.008***	0.009***
	(3.23)	(2.97)	(3.68)	(3.55)	(3.70)
Non-AI	0.010***	0.018***	0.019***	0.019***	0.020***
	(7.40)	(7.62)	(7.05)	(6.21)	(5.62)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel E. Total Factor Productivity		
AI (Exploitative)	0.002**	0.002	0.006**	0.009**	0.006
	(2.01)	(1.19)	(2.31)	(2.53)	(1.27)
AI (Explorative)	0.003**	0.004**	0.003	0.005	0.007
	(2.38)	(2.02)	(0.92)	(1.15)	(1.50)
Non-AI	0.014***	0.015***	0.005	0.004	0.006
	(5.69)	(6.60)	(0.72)	(0.77)	(1.34)
Obs.	106,627	96,654	88,705	81,710	74,058

Table 7: First Stage Regressions

This table reports the first stage regressions using patent examiners' leniency to instrument the value of the granted patent filings. The sample period is 2001 to 2016. We calculate examiner leniency following Farre-Mensa, Hegde, and Ljungqvist (2020) for each patent application and aggregate the leniency ratio by summing it across all applications (granted and rejected) to the firm-year. The dependent variables are the aggregated market value of AI and non-AI patents granted in year t by firm i scaled by total assets. We control for the number of applications filed (both granted and rejected) for both AI patents and Non-AI patents. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. All potentially unbounded variables are winsorised at 1% level. Detailed variable definitions are provided in Appendix Table A.1.

	θ^{AI}	θ^{non-AI}
	(1)	(2)
AI Patent Examiner Approval Rates	0.520***	
	(8.30)	
N(AI Applications)	-0.043	
	(-0.70)	
Non-Patent Examiner Approval Rates		0.135***
		(6.65)
N(Non-AI Applications)		0.024
		(1.20)
Ln(Assets)	-0.056***	-0.034***
	(-5.77)	(-8.30)
Ln(Firm Age)	-0.027***	0.003
	(-2.60)	(0.75)
Year FE	✓	✓
Firm FE	✓	✓
Obs.	55,096	55,096
R^2	0.76	0.72
Kleibergen-Paap Wald F statistic	68	819

Table 8: Investment Regressions

This table shows the second-stage results for our 2SLS analysis. The dependent variables are various investment-related variables. Detailed variable definitions are provided in Appendix Table A.1. The sample period is 2001 to 2016. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. All potentially unbounded variables are winsorised at 1% level.

Panel A - 2SLS for AI patents

	XRD/AT	CAPX/AT	Vert. Integ.	d2vscope	New TM	Acquirer	Target
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
θ^{AI}	0.006	-0.002	-0.040**	-0.211	0.045	0.005	-0.014**
	(1.16)	(-0.95)	(-2.08)	(-0.79)	(1.14)	(0.61)	(-2.10)
N(AI Applications)	-0.000	0.001	0.016*	0.100	-0.013	-0.003	0.002
	(-0.13)	(1.52)	(1.72)	(0.81)	(-0.72)	(-0.95)	(0.69)
Ln(Assets)	-0.035***	-0.001*	0.048***	0.837***	0.090***	0.035***	-0.002
	(-22.62)	(-1.73)	(6.59)	(11.28)	(13.04)	(16.03)	(-1.18)
Ln(Firm Age)	0.005***	-0.005***	0.034***	0.163*	0.009	0.005*	0.013***
	(4.24)	(-6.46)	(2.87)	(1.85)	(0.90)	(1.74)	(7.68)
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Obs.	55,096	55,096	54,577	51,594	55,096	55,096	55,096
R^2	0.10	0.00	0.00	0.02	0.01	0.01	0.00

Panel B - 2SLS for non-AI patents

	XRD/AT	CAPX/AT	Vert. Integ.	d2vscope	New TM	Acquirer	Target
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
θ^{non-AI}	-0.077**	0.022**	-0.056	-0.040	0.369***	-0.039*	-0.044
	(-2.26)	(2.08)	(-0.55)	(-0.04)	(2.64)	(-1.68)	(-1.31)
N(Non-AI Applications)	0.025***	-0.003**	0.015	0.059	-0.052**	0.005	0.001
	(4.35)	(-2.01)	(0.94)	(0.36)	(-2.35)	(1.29)	(0.27)
Ln(Assets)	-0.036***	-0.000	0.050***	0.855***	0.100***	0.034***	-0.003
	(-19.21)	(-0.32)	(6.24)	(10.21)	(12.33)	(14.65)	(-1.63)
Ln(Firm Age)	0.006***	-0.005***	0.036***	0.171*	0.007	0.005*	0.014***
	(4.58)	(-6.46)	(3.02)	(1.95)	(0.68)	(1.72)	(7.87)
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Obs.	55,096	55,096	54,577	51,594	55,096	55,096	55,096
R^2	0.03	-0.01	0.00	0.02	-0.00	0.01	0.00

Table 9: Outcome Regressions

This table shows the second-stage results for our 2SLS analysis. The dependent variables are various firm outcomes. Detailed variable definitions are provided in Appendix Table A.1. The sample period is 2001 to 2016. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. All potentially unbounded variables are winsorised at 1% level.

Panel A - 2SLS for AI patents

	Total Q	OI/AT	VOL
	(1)	(2)	(3)
θ^{AI}	0.310***	0.004	2.486**
	(2.59)	(0.35)	(2.00)
N(AI Applications)	-0.137**	-0.004	-1.135*
	(-2.43)	(-0.68)	(-1.93)
Ln(Assets)	0.174***	0.087***	-4.949***
	(5.71)	(21.58)	(-16.00)
Ln(Firm Age)	-0.699***	0.000	-3.366***
	(-16.67)	(0.02)	(-9.07)
Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Obs.	54,784	55,095	54,696
R^2	0.04	0.08	0.02

Panel B - 2SLS for Non-AI patents

	Total Q	OI/AT	VOL
	(1)	(2)	(3)
θ^{non-AI}	0.934*	0.160**	14.860**
	(1.73)	(2.13)	(2.26)
N(Non-AI Applications)	-0.160*	-0.043***	-2.600**
	(-1.82)	(-3.43)	(-2.52)
Ln(Assets)	0.186***	0.090***	-4.608***
	(5.33)	(17.68)	(-12.01)
Ln(Firm Age)	-0.712***	-0.002	-3.496***
	(-16.98)	(-0.43)	(-9.33)
Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Obs.	54,784	55,095	54,696
R^2	0.05	0.05	0.00

Table 10: Knowledge Accumulation, Knowledge Spillover: AI vs. Non-AI

This table presents the results of a Poisson regression analyzing the knowledge accumulation and spillover effects of AI patents versus non-AI patents. The dependent variable is the number of patents filed in year t by firm i. "Pat. Stock" is defined as the natural logarithm of one plus the number of patents filed during the period $t-10$ to $t-1$. "Spilltech" measures Technological Spillovers, constructed in the spirit of Bloom, Schankerman, and Van Reenen (2013), and is defined as the number of patents filed during the period $t-10$ to $t-1$ by firm j, weighted by technological similarity with firm i. Detailed variable definitions are provided in Appendix Table A.1. The T-statistics, adjusted for clustered standard errors at the firm level, are reported in parentheses. ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively. The sample period spans from 1976 to 2016. The number of observations may vary due to singleton observations.

Panel A - AI Patents and non-AI Patents

	AI + Non-AI			AI			Non-AI		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AI Pat. Stock	0.068***	0.083***	0.071***	0.309***	0.319***	0.306***	0.047***	0.058***	0.048***
	(6.34)	(7.49)	(6.35)	(14.89)	(15.76)	(14.44)	(4.64)	(5.79)	(4.68)
Non-AI Pat. Stock	0.800***	0.776***	0.792***	0.136***	0.118***	0.141***	0.854***	0.836***	0.849***
	(27.46)	(25.99)	(26.38)	(3.39)	(2.97)	(3.43)	(32.94)	(31.41)	(31.79)
Spilltech (AI)	0.260***		0.219***	0.186***		0.232**	0.218***		0.193***
	(6.80)		(4.06)	(3.83)		(2.26)	(5.45)		(3.59)
Spilltech (non-AI)		0.293***	0.080		0.196***	-0.064		0.233***	0.052
		(6.34)	(1.23)		(3.39)	(-0.52)		(4.83)	(0.81)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	77,227	77,227	77,227	34,000	34,000	34,000	75,005	75,005	75,005

Panel B - Heterogeneous Effects on Different Types of Firms

Dep=All Pat	AI Firm			Non-AI Firm		
	(1)	(2)	(3)	(4)	(5)	(6)
Pat. Stock	0.518***	0.514***	0.522***	0.531***	0.527***	0.526***
	(26.43)	(26.07)	(26.55)	(20.49)	(19.14)	(19.23)
Spilltech (AI)	0.299***		0.342***	0.060*		0.024
	(3.86)		(3.76)	(1.67)		(0.44)
Spilltech (non-AI)		0.252	-0.178		0.074**	0.056
		(1.38)	(-0.81)		(2.11)	(1.02)
Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Obs.	19,206	19,206	19,206	56,888	56,888	56,888

Table 11: Industry Outcomes

This table presents the relationship between AI patent intensity and industry-level outcomes. We follow and use data from Hoberg and Phillips (2024) to measure industry sales and concentration. The analysis is conducted at the industry-year level.

$$Y_{I,t+\tau} = \beta_0 + \beta_1 \frac{\text{AI Pat.}_{I,t}}{\text{All Pat.}_{I,t}} + \delta X_{I,t} + \alpha_I + \delta_t + \epsilon_{I,t+\tau}$$

Each firm's sales and employment are weighted based on the text loading into each of the 300 industries using text spatial modeling. We control for ln(Sales), ln(Employment), and ln(Total Patents) filed in year t. Industry and year fixed effects are included in all regressions. T-statistics adjusted for clustered standard errors at the industry level are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. All potentially unbounded variables are winsorized at the 1% level. Detailed variable definitions are provided in Appendix Table A.1. The sample period is from 1988 to 2016.

	t+1	t+2	t+3	t+4	t+5
			Panel A - Ln(Sales)		
AI Pat./All Pat.	0.120***	0.220***	0.222***	0.234***	0.208**
	(2.92)	(3.53)	(2.88)	(2.64)	(2.21)
Obs.	8,376	8,077	7,778	7,480	7,181
			Panel B - Ln(Employment)		
AI Pat./All Pat.	0.159***	0.247***	0.313***	0.308***	0.329***
	(3.96)	(4.01)	(4.00)	(3.88)	(3.81)
Obs.	8,376	8,077	7,778	7,480	7,181
			Panel C - HHI (All firms)		
AI Pat./All Pat.	0.071***	0.071***	0.039**	0.030*	0.024
	(3.28)	(3.57)	(2.09)	(1.74)	(1.40)
Obs.	8,376	8,077	7,778	7,480	7,181
			Panel D - HHI (AI firms)		
AI Pat./All Pat.	-0.139***	-0.124***	-0.141***	-0.109***	-0.097***
	(-3.89)	(-3.28)	(-3.75)	(-3.03)	(-2.62)
Obs.	8,237	7,944	7,660	7,371	7,081
			Panel E - HHI (non-AI firms)		
AI Pat./All Pat.	0.058**	0.069***	0.044**	0.035*	0.031*
	(2.39)	(3.13)	(2.21)	(1.88)	(1.69)
Obs.	8,376	8,077	7,778	7,480	7,181

Appendix A.

Appendix A.1. Innovation Novelty Measures

In this section, we present the technological novelty measures central to our analysis, closely following the methodology outlined in Verhoeven, Bakker, and Veugelers (2016). Below, we detail the process.

Appendix A.1.1. Novelty in Recombination

We define inventions as novel in recombination when they introduce unprecedented combinations of components and principles to achieve specific outcomes. To quantify this, we use the technological classifications assigned to patents, serving as proxies for the components and principles involved. By analyzing the pairwise combinations of group-level IPC (International Patent Classification) codes, we assess whether these combinations have previously appeared in the patent database before the patent's application year. A patent is classified as having "Novelty in Recombination (NR)" if it contains at least one pair of IPC groups that had never been combined before.

In contrast to Fleming (2007), who employed the US Patent Office Classification (USPC) system to evaluate inventors' generative creativity, we opt for the IPC classification system for several compelling reasons. The IPC system is more comprehensive, as it applies to all patent applications globally, unlike the USPC, which is confined to patents filed with the USPTO. Furthermore, the IPC system is more adept at assessing the recombinant nature of an invention because it categorizes patents based on the full technological content of the application, whereas the USPC emphasizes the scope of protection. Additionally, the high degree of disaggregation in the USPC system can lead to an overestimation of novelty, with nearly half of all patents appearing novel under this system.

Appendix A.1.2. Novelty in Knowledge Origins

Our analysis of novelty in knowledge origins focuses on identifying patents that incorporate technological or scientific knowledge from previously unexplored domains. By examining

the references cited within patent documents, we trace the origins of the knowledge that these inventions draw upon. Through backward citation analysis, we identify inventions that establish novel connections across different fields of knowledge — an aspect that existing backward citation measures often overlook. To evaluate this, we scrutinize the patents cited by the focal patent, identifying their IPC classifications, and construct "backward citation pairs" of IPC codes. We then determine if a particular combination is novel by comparing each pair against previously established pairs. A patent is considered to possess "Novelty in Technological Origins (NTO)" if it creates a new combination between its own IPC code and an IPC code from its referenced patents that had not existed before the patent's application year.

Appendix A.1.3. Novelty from Basic Science

To trace the scientific knowledge serving as prior art in an invention, we analyze the scientific documents cited in patents. In Verhoeven, Bakker, and Veugelers (2016), the authors integrate IPC codes from patent documents with Web of Science (WOS) journal classifications of the cited scientific articles. This process begins by extracting Non-Patent References (NPRs) from patents and linking them to the WOS subject categories of the journals where these references were published. The resulting pairs of IPC classes and scientific categories introduced by patent applications are then compared to all previously established combinations. However, since the majority of patents (over 86%) do not cite scientific papers and thus remain undefined in this context, this measure proves too coarse. Therefore, we adopt a simpler approach, using the count of scientific papers cited by the patents as our measure of the technological significance derived from basic science.

Appendix B. Appendix Tables

Table A.1: Variable Definitions

Variable Name	Abbrev.	Description
Patent metrics		
Claims		Number of claims in the patent
Scope		Unique number of IPC 4-digit classifications of a patent
Originality		HHI index of cited patents' IPC4 classes
Generality		HHI index of citing patents' IPC4 classes
Forward		Forward citations, measured as number of US patents citing the patent
BK10		Indicator=1 if it is a top 10% patents based on 5-year similarity q=Forward Similarity/Backward Similarity as in Kelly et al. (2021)
ξ		Market value of patent (Kogan et al., 2017)
Novelty: Recomb		Indicator=1 if the patent consititue a new recombination of IPCs, see section A.1
Novelty: Knowledge Origin		Indicator=1 if the patent cites a patent from a previously unlinked IPC, see section A.1
Sci. Cit		Number of citations to scientific literature by the patent
Exploitative		Indicator =1 if more than 90% of the focal patent's backward citations are the firm's own patents or patents the firm has cited before
Explorative		Indicator =1 if less than 10% of the focal patent's backward citations are the firm's own patents or patents the firm has cited before
Firm growth		
Profits		Sales minus cost of goods sold [COMPUSTAT: SALE - COGS deflated by CPI]
Sales		Sales (COMPUSTAT: sale)
Capital Stock		[COMPUSTAT: PPEGT deflated by the NIPA price of equipment]
Employment		[COMPUSTAT: EMP]
Total Factor Productivity	TFP	Revenue-based TFP constructed using methodology of Olley and Pakes (1996) applied using the procedure in İmrohoroğlu and Tüzel (2014)
Firm characteristics		
Ln(Total Assets)		Natural log of (Firm's total asset [COMPUSTAT: AT])
Ln(Market Cap)		Natural log of total market capitalisation [COMPUSTAT: CSHO×PRCC_F]
Tobin's Q		Sum of total assets plus market value of equity minus book value of equity divided by total assets [COMPUSTAT: (AT+CSHO× PRCC_F - CEQ) / AT)].
Total Q		Tobin's Q adjusted for intangible assets Peters and Taylor (2017)
Leverage		Firm's total debt divided by total assets [COMPUSTAT: (DLTT + DLC)/AT]
Return on Assets	ROA	Net Income divided by total assets [COMPUSTAT: NI / AT]
Asset Growth		Asset growth from last fiscal year end [COMPUSTAT: ($SALE_t$/$SALE_{(t-1)}$ -1)]
Sales Growth		Sales growth from last fiscal year end [COMPUSTAT: ($SALE_t$/$SALE_{(t-1)}$ -1)]
Profitability	OI/AT	Operating income divided by total assets [COMPUSTAT: OI/AT]
Cash Holdings		[COMPUSTAT: CHE/AT]
Dividends		Firm's total dividends issued [COMPUSTAT: DVT/AT]
Capital Expenditure	CAPX	Capital expenditures divided by total assets [COMPUSTAT: CAPX/AT]
Tangibility	PPE	Property, plant, and equipment scaled by asset [COMPUSTAT: PPENT/AT]
R&D	R&D	Research and development expenses divided by total assets [COMPUSTAT: XRD/AT]
Missing R&D	XRD	Indicator variable equal to 1 if R&D expense is missing, zero otherwise
Advertising	XAD	Research and development expenses divided by total assets [COMPUSTAT: XRD/AT]
Dividends		Dividends issued scaled by total assets [COMPUSTAT DVT / AT]
Firm Age		Number of years since the firm first appears in CRSP database
Idiosyncratic Volatility	VOL $\sigma_{i,t}$	Sum of squared abnormal returns [CRSP DSF: $\sum_{d\in t}(r_i - r_m)^2$]
Instutional Ownership	Inst. Own	The percentage of Instutional Ownership [Refinitiv S34]
Acquirer		Acquirer indicator variable that takes value of if the firm acquires one or more firms in t [Refinitiv SDC]
Target		Target indicator variable that takes value of if the firm is acquired in t [Refinitiv SDC]
Equity Issue		Indicator variable that takes value of one if firm issues equity in year t [Refinitiv SDC]
Debt Issue		Indicator variable that takes value of one if firm issues debt in year t [Refinitiv SDC]
Repurchase		Amount of repurchase measured by decrease in share outstanding [CRSP: SHROUT] times price [CRSP: PRC]
HHI		Sales HHI for each SIC4-year [Compustat]
Scope		Hoberg and Phillips (2024) Firm Product Scope measure
Verical Integration	vertinteg	Frésard, Hoberg, and Phillips (2019) measure
New Trademark	New TM	Indicator variable that takes value of one if firm files a new trademark that shows commercialization date in t [USPTO]

Table A.2: Top Cited AI patents used for Training (Seed Patents)

This table delineates the three most-cited AI patents within each domain, based on citations accumulated by the conclusion of 2022. Certain patents appear across multiple categories, reflecting their applicability to various domains.

Panel A - Machine Learning

patnum	idate	title	fcite
6081750	20000627	Ergonomic man-machine interface incorporating adaptive pattern recognition based control system	694
6021403	20000201	Intelligent user assistance facility	547
5901246	19990504	Ergonomic man-machine interface incorporating adaptive pattern recognition based control system	387

Panel B - Evolution Computation

patnum	idate	title	fcite
6941287	20050906	Distributed hierarchical evolutionary modeling and visualization of empirical data	135
6502081	20021231	System and method for classifying legal concepts using legal topic scheme	120
5897629	19990427	Apparatus for solving optimization problems and delivery planning system	110

Panel C - NLP

patnum	idate	title	fcite
6804330	20041012	Method and system for accessing CRM data via voice	1626
6021403	20000201	Intelligent user assistance facility	547
5873056	19990216	Natural language processing system for semantic vector representation which accounts for lexical ambiguity	506

Panel D - Speech

patnum	idate	title	fcite
6804330	20041012	Method and system for accessing CRM data via voice	1626
6081750	20000627	Ergonomic man-machine interface incorporating adaptive pattern recognition based control system	694
6021403	20000201	Intelligent user assistance facility	547

Panel E - Computer Vision

patnum	idate	title	fcite
6081750	20000627	Ergonomic man-machine interface incorporating adaptive pattern recognition based control system	694
6021403	20000201	Intelligent user assistance facility	547
5873056	19990216	Natural language processing system for semantic vector representation which accounts for lexical ambiguity	506

Panel F - Knowledge Processing

patnum	idate	title	fcite
6804330	20041012	Method and system for accessing CRM data via voice	1626
6081750	20000627	Ergonomic man-machine interface incorporating adaptive pattern recognition based control system	694
6021403	20000201	Intelligent user assistance facility	547

Panel G - Planning/Control

patnum	idate	title	fcite
6804330	20041012	Method and system for accessing CRM data via voice	1626
6081750	20000627	Ergonomic man-machine interface incorporating adaptive pattern recognition based control system	694
6021403	20000201	Intelligent user assistance facility	547

Panel H - AI Hardware

patnum	idate	title	fcite
6804330	20041012	Method and system for accessing CRM data via voice	1626
6081750	20000627	Ergonomic man-machine interface incorporating adaptive pattern recognition based control system	694
5276735	19940104	Data enclave and trusted path system	555

Table A.3: Top Cited AI patents

This table delineates the three most-cited AI patents within each domain, based on citations accumulated by the conclusion of 2022. Certain patents appear across multiple categories, reflecting their applicability to various domains.

Panel A - Machine Learning

patnum	idate	title	fcite
6323846	20011127	Method and apparatus for integrating manual input	2752
7663607	20100216	Multipoint touchscreen	2513
5880411	19990309	Object position detector with edge motion feature and gesture recognition	1723

Panel B - Evolution Computation

patnum	idate	title	fcite
6571282	20030527	Block-based communication in a communication services patterns environment	1629
5845266	19981201	Crossing network utilizing satisfaction density profile with price discovery features	989
7181438	20070220	Database access system	878

Panel C - NLP

patnum	idate	title	fcite
5848396	19981208	Method and apparatus for determining behavioral profile of a computer user	2065
5948040	19990907	Travel reservation information and planning system	2048
6850252	20050201	Intelligent electronic appliance system and method	1935

Panel D - Speech

patnum	idate	title	fcite
5794207	19980811	Method and apparatus for a cryptographically assisted commercial network system designed to facilitate buyer-driven conditional purchase offers	2106
5848396	19981208	Method and apparatus for determining behavioral profile of a computer user	2065
5948040	19990907	Travel reservation information and planning system	2048

Panel E - Computer Vision

patnum	idate	title	fcite
6323846	20011127	Method and apparatus for integrating manual input	2752
7663607	20100216	Multipoint touchscreen	2513
6177931	20010123	Systems and methods for displaying and recording control interface with television programs, video, advertising information and program scheduling information	2303

Panel F - Knowledge Processing

patnum	idate	title	fcite
6323846	20011127	Method and apparatus for integrating manual input	2752
6177931	20010123	Systems and methods for displaying and recording control interface with television programs, video, advertising information and program scheduling information	2303
5794207	19980811	Method and apparatus for a cryptographically assisted commercial network system designed to facilitate buyer-driven conditional purchase offers	2106

Panel G - Planning/Control

patnum	idate	title	fcite
5892900	19990406	Systems and methods for secure transaction management and electronic rights protection	2965
6323846	20011127	Method and apparatus for integrating manual input	2752
6177931	20010123	Systems and methods for displaying and recording control interface with television programs, video, advertising information and program scheduling information	2303

Panel H - AI Hardware

patnum	idate	title	fcite
5892900	19990406	Systems and methods for secure transaction management and electronic rights protection	2965
6323846	20011127	Method and apparatus for integrating manual input	2752
7663607	20100216	Multipoint touchscreen	2513

Table A.4: Top Firms

This table presents the firms (patent assignees) holding the highest number of AI patents, incorporating both public and private firms using the disambiguated assignee names in Patentsview. AI subcategories are shown and the sum of subcategories might not match the total number of AI patents due to the cross-categorization of some patents.

	assignee	All AI	ML	Evo	NLP	Speech	CV	KP	P/C	Hardware
1	International Business Machines Corporation	56,434	6,307	2,296	9,370	3,605	8,903	36,737	38,335	30,275
2	Microsoft Corporation	25,761	3,211	885	5,877	2,737	6,195	16,797	18,833	13,141
3	GOOGLE LLC	13,158	1,390	442	4,019	1,912	4,428	8,564	10,177	5,281
4	Intel Corporation	8,686	696	160	423	321	1,514	3,486	2,455	5,356
5	Samsung Electronics Co., Ltd.	8,428	652	152	641	825	3,959	2,965	2,762	2,408
6	Amazon Technologies, Inc.	7,531	586	157	924	634	1,233	4,290	5,651	2,845
7	Canon Kabushiki Kaisha	6,794	302	60	517	359	5,061	1,548	1,320	1,110
8	Apple Inc.	5,688	248	61	772	777	1,739	2,710	3,288	1,886
9	SONY CORPORATION	5,589	442	75	455	485	3,084	1,982	1,971	1,215
10	Hewlett-Packard Development Company, L.P.	5,561	468	179	494	185	1,647	2,805	2,874	2,441
11	Oracle International Corporation	5,269	375	165	826	121	412	3,778	4,056	3,205
12	FUJITSU LIMITED	4,985	483	132	536	346	1,919	2,315	2,030	1,738
13	AT&T Intellectual Property I, L.P.	4,715	487	121	824	851	796	2,646	3,745	1,365
14	General Electric Company	4,477	723	150	136	58	1,993	2,350	2,341	822
15	QUALCOMM Incorporated	4,310	442	86	148	233	1,174	2,344	1,781	1,516
16	Xerox Corporation	3,917	498	142	967	356	2,253	1,817	2,059	1,256
17	HITACHI, LTD.	3,887	421	93	363	207	1,011	1,808	1,884	1,444
18	Cisco Technology, Inc.	3,822	433	87	259	177	384	2,158	2,374	1,724
19	KABUSHIKI KAISHA TOSHIBA	3,707	363	74	530	432	1,807	1,467	1,235	1,118
20	SIEMENS AKTIENGESELLSCHAFT	3,663	599	131	178	133	1,676	1,922	1,783	883
21	Facebook, Inc.	3,265	329	89	818	235	757	2,258	2,893	1,058
22	NEC CORPORATION	3,106	486	118	377	379	1,233	1,612	1,250	1,119
23	Sun Microsystems Inc.	2,970	167	66	255	52	264	1,484	1,302	1,985
24	SAP AG	2,921	184	66	497	72	217	2,137	2,451	1,522
25	RICOH COMPANY, LTD.	2,689	155	41	393	173	1,513	797	1,087	650
26	TELEFONAKTIEBOLAGET LM ERICSSON (PUBL)	2,583	298	68	77	110	272	1,638	1,392	678
27	SAP SE	2,486	223	83	448	79	258	1,920	2,009	1,439
28	Adobe Systems Incorporated	2,460	230	34	472	125	1,179	1,263	1,412	791
29	HONEYWELL INTERNATIONAL INC.	2,265	295	77	77	76	510	1,446	1,509	466
30	Texas Instruments Incorporated	2,208	332	65	162	198	552	1,020	605	1,090
31	The Boeing Company	2,173	342	91	120	54	608	1,579	1,379	550
32	YAHOO HOLDINGS, INC.	1,963	270	89	664	203	495	1,511	1,790	836
33	EMC Corporation	1,960	134	46	122	25	163	1,220	1,175	1,084
34	BANK OF AMERICA CORPORATION	1,915	151	64	146	43	182	1,178	1,694	509
35	Micron Technology, Inc.	1,885	70	12	32	11	272	397	226	1,359
36	salesforce.com, inc.	1,861	98	21	353	57	102	1,612	1,820	1,613
37	Motorola, Inc.	1,768	290	52	182	289	308	825	765	785
38	Symantec Corporation	1,699	153	20	163	25	218	1,213	1,158	647
39	Advanced Micro Devices, Inc.	1,699	144	49	20	25	168	643	505	1,130
40	LG Electronics Inc.	1,672	54	15	128	191	569	600	651	330
41	GM GLOBAL TECHNOLOGY OPERATIONS LLC	1,660	221	41	71	76	369	942	1,200	252
42	EMC IP Holding Company LLC	1,596	161	59	89	12	156	1,034	948	901
43	EASTMAN KODAK COMPANY	1,594	99	19	66	44	1,314	367	350	223
44	ELECTRONICS AND TELECOMMUNICATIONS RESEARCH INSTITUTE	1,593	269	54	182	187	741	878	655	562
45	Robert Bosch GmbH	1,574	121	30	70	65	395	904	955	247
46	EBAY INC.	1,571	93	36	289	66	325	941	1,397	429
47	Verizon Patent and Licensing Inc.	1,567	70	23	93	68	171	792	1,266	354
48	MITSUBISHI HEAVY INDUSTRIES, LTD.	1,562	230	34	94	121	535	690	588	472
49	Koninklijke Philips N.V.	1,561	189	51	49	32	1,033	718	575	219
50	FORD GLOBAL TECHNOLOGIES, LLC	1,514	193	24	31	50	253	795	1,156	165

Table A.5: CEO Determinants

This table presents the firm and CEO level determinants of AI patent filings. In Columns 1 to 2, we estimate OLS Regressions, and the dependent variable is an indicator if the firm has filed at least one AI patent in the given year. In Columns 3 to 4, we estimate Poisson regression with dependent variable being the number of AI patents filed in the given year. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. All potentially unbounded variables are winsorised at 1% level. Detailed variable definitions are provided in Appendix Table A.1. The sample period is 1976 to 2020.

	I(AI)		N(AI)	
	(1)	(2)	(3)	(4)
Ln(Assets)	0.061***	0.037***	0.558***	0.191***
	(14.44)	(5.97)	(13.15)	(2.68)
Tobin's Q	0.022***	0.006**	0.136***	0.018
	(6.60)	(2.08)	(4.60)	(0.54)
PPE/AT	-0.042	0.047	-0.204	0.585
	(-1.14)	(1.31)	(-0.47)	(1.26)
CEO Age	-0.002***	-0.001	-0.014*	-0.005
	(-2.92)	(-1.37)	(-1.79)	(-0.71)
CEO tenure	-0.001*	-0.000	-0.002	0.002
	(-1.91)	(-0.65)	(-0.26)	(0.26)
Male	0.030	0.032*	-0.051	0.311***
	(1.54)	(1.78)	(-0.37)	(2.69)
OC Holder67	-0.012**	0.000	-0.010	0.028
	(-1.99)	(0.00)	(-0.16)	(0.68)
Founder	0.049***	0.031	0.590***	-0.143
	(2.65)	(1.36)	(2.95)	(-0.95)
Ivy League	-0.012	0.004	-0.241**	0.074
	(-1.20)	(0.46)	(-2.25)	(1.38)
MBA	0.019**	0.001	0.230**	0.081
	(2.00)	(0.10)	(2.47)	(1.22)
Ph.D	0.031	0.001	0.278**	0.088
	(1.58)	(0.09)	(2.10)	(1.24)
Tech Education	-0.028	0.006	-0.212	0.157*
	(-0.89)	(0.16)	(-1.28)	(1.86)
No School Info.	0.001	-0.003	-0.620***	-0.041
	(0.05)	(-0.22)	(-3.58)	(-0.37)
General Ability Index	0.004*	-0.003	0.043**	0.005
	(1.71)	(-1.53)	(2.10)	(0.38)
Military Experience	0.033	0.032	0.220	-0.176*
	(1.42)	(1.47)	(1.14)	(-1.75)
Inventor CEO	0.037***	0.006	-0.011	0.005
	(2.97)	(0.55)	(-0.08)	(0.06)
Duality	0.011	0.012**	0.041	0.062
	(1.36)	(2.00)	(0.51)	(1.07)
Non-AI Patents	0.001***	0.001***	0.003***	0.003***
	(12.50)	(6.52)	(6.63)	(5.47)
SIC4 FE	✓		✓	
Year FE	✓	✓	✓	✓
Firm FE		✓		✓
Obs.	28,850	28,699	23,751	12,013
R^2	0.41	0.67		

Table A.6: Firm Growth - Explorative vs. Exploitative

The table repeats the analysis of Table 5, but disaggregate all patents (regardless of AI or non-AI) into exploitative and explorative. The rest of the specifications are the same as Table 5. Detailed variable definitions are provided in Appendix Table A.1.

	t+1	t+2	t+3	t+4	t+5
			Panel A. Profits		
Exploitative	0.008***	0.014***	0.024***	0.030***	0.032***
	(3.85)	(3.69)	(4.21)	(4.47)	(4.25)
Explorative	0.012***	0.021***	0.019***	0.021***	0.022***
	(5.72)	(5.63)	(2.91)	(3.36)	(3.39)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel B. Sales		
Exploitative	0.006***	0.010***	0.016***	0.020***	0.024***
	(2.61)	(2.65)	(4.15)	(5.07)	(4.61)
Explorative	0.016***	0.026***	0.027***	0.029***	0.029***
	(7.65)	(6.74)	(5.56)	(4.86)	(4.54)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel C. Capital		
Exploitative	0.002**	0.006***	0.012***	0.016***	0.017***
	(2.12)	(2.76)	(4.53)	(5.25)	(4.99)
Explorative	0.017***	0.028***	0.031***	0.034***	0.036***
	(7.57)	(7.52)	(6.94)	(6.19)	(5.85)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel D. Employment		
Exploitative	0.002**	0.006***	0.008***	0.010***	0.012***
	(2.40)	(3.12)	(3.08)	(3.33)	(3.20)
Explorative	0.012***	0.020***	0.021***	0.021***	0.021***
	(8.39)	(7.51)	(6.42)	(5.25)	(4.72)
Obs.	161,598	147,754	135,616	124,953	113,063
			Panel E. Total Factor Productivity		
Exploitative	0.013***	0.014***	0.019***	0.022***	0.023***
	(5.64)	(4.12)	(4.39)	(4.34)	(3.61)
Explorative	0.010***	0.012***	-0.001	-0.001	0.001
	(3.87)	(5.85)	(-0.07)	(-0.26)	(0.24)
Obs.	106,627	96,654	88,705	81,710	74,058

Table A.7: Firm Growth - Subcategories

The table repeats the analysis of Table 5, but disaggregate AI patents into their subcategories. The rest of the specifications are the same as Table 5. Detailed variable definitions are provided in Appendix Table A.1.

	t+1	t+2	t+3	t+4	t+5
Panel A. Profits					
Machine Learning	0.010**	0.008	0.005	-0.000	-0.002
	(2.48)	(1.57)	(0.74)	(-0.03)	(-0.35)
Evolutionary Computation	-0.003*	-0.003	-0.002	-0.003	-0.003
	(-1.67)	(-1.46)	(-1.05)	(-1.48)	(-1.19)
Natural Language Processing	0.006	-0.005	-0.005	-0.006	-0.006
	(1.59)	(-0.80)	(-0.94)	(-1.39)	(-1.04)
Speech	-0.004	0.008**	0.009**	0.009***	0.008*
	(-0.72)	(1.97)	(2.52)	(2.63)	(1.89)
Vision	-0.004*	0.004	0.005	0.003	0.004
	(-1.86)	(0.90)	(1.48)	(1.04)	(0.97)
Knowledge Processing	0.002	-0.000	0.008	0.016	0.009
	(0.38)	(-0.03)	(0.67)	(1.22)	(0.65)
Planning/Control	-0.003	0.006	-0.001	-0.001	0.001
	(-0.50)	(0.65)	(-0.09)	(-0.08)	(0.09)
AI Hardware	-0.000	0.001	-0.001	-0.004	-0.001
	(-0.01)	(0.10)	(-0.16)	(-0.59)	(-0.10)
Non-AI	0.013***	0.021***	0.026***	0.028***	0.030***
	(6.62)	(5.82)	(4.32)	(4.03)	(3.91)
Obs.	158,343	141,643	127,036	114,292	103,116
Panel B. Sales					
Machine Learning	0.002	-0.002	-0.004	-0.009	-0.013
	(0.54)	(-0.37)	(-0.68)	(-1.31)	(-1.52)
Evolutionary Computation	-0.000	-0.001	0.000	-0.000	-0.001
	(-0.35)	(-0.22)	(0.06)	(-0.10)	(-0.39)
Natural Language Processing	0.002	0.001	-0.002	-0.004	-0.003
	(0.63)	(0.32)	(-0.36)	(-1.03)	(-0.81)
Speech	0.001	-0.001	0.001	0.005	0.003
	(0.44)	(-0.13)	(0.29)	(1.46)	(1.07)
Vision	-0.003	0.001	0.005	0.006*	0.005*
	(-1.53)	(0.26)	(1.42)	(1.66)	(1.66)
Knowledge Processing	-0.003	0.000	0.007	0.009	0.002
	(-0.62)	(0.05)	(0.78)	(0.85)	(0.19)
Planning/Control	0.005	0.014	0.012	0.007	0.011
	(0.85)	(1.56)	(1.43)	(0.66)	(1.24)
AI Hardware	0.004	-0.003	-0.006	-0.002	0.003
	(1.31)	(-0.56)	(-1.05)	(-0.32)	(0.49)
Non-AI	0.016***	0.027***	0.030***	0.031***	0.031***
	(7.23)	(6.93)	(6.25)	(5.31)	(4.46)
Obs.	158,343	141,643	127,036	114,292	103,116
Panel C. Capital					
Machine Learning	-0.004	-0.007**	-0.005	-0.006	-0.006
	(-1.51)	(-2.10)	(-1.34)	(-1.55)	(-1.47)
Evolutionary Computation	0.001	0.001	-0.001	-0.001	-0.001
	(0.58)	(0.42)	(-0.19)	(-0.32)	(-0.14)
Natural Language Processing	-0.002	-0.005	-0.007**	-0.006	-0.000
	(-0.76)	(-1.09)	(-2.07)	(-1.10)	(-0.10)
Speech	0.001	-0.002	0.000	-0.000	-0.004
	(0.42)	(-0.78)	(0.05)	(-0.15)	(-1.44)
Vision	0.011	0.016	0.008	0.007	0.008
	(1.34)	(1.46)	(1.61)	(1.57)	(1.47)
Knowledge Processing	-0.004	-0.003	0.001	-0.000	-0.009
	(-1.06)	(-0.59)	(0.17)	(-0.05)	(-0.96)
Planning/Control	0.001	0.012**	0.015**	0.017**	0.021**
	(0.23)	(2.01)	(2.55)	(2.04)	(2.41)
AI Hardware	0.009**	0.006	0.003	0.004	0.003
	(2.57)	(1.30)	(0.62)	(0.61)	(0.50)
Non-AI	0.012***	0.023***	0.031***	0.034***	0.036***
	(7.96)	(8.09)	(8.27)	(7.66)	(6.73)
Obs.	158,343	141,643	127,036	114,292	103,116
Panel D. Employment					
Machine Learning	-0.001	-0.001	-0.003	-0.003	-0.005*
	(-0.98)	(-0.55)	(-0.94)	(-1.13)	(-1.70)
Evolutionary Computation	0.001	0.000	0.000	-0.001	-0.001
	(0.74)	(0.11)	(0.12)	(-0.41)	(-0.19)
Natural Language Processing	-0.001	-0.001	-0.003	-0.003	0.003
	(-0.46)	(-0.43)	(-1.29)	(-0.74)	(0.93)
Speech	0.002	-0.000	0.001	0.002	-0.004
	(1.01)	(-0.07)	(0.53)	(0.82)	(-1.46)
Vision	-0.004***	-0.003*	0.004	0.005*	0.006*
	(-3.36)	(-1.72)	(1.15)	(1.69)	(1.72)
Knowledge Processing	-0.001	0.001	0.003	0.006	-0.004
	(-0.16)	(0.17)	(0.46)	(0.76)	(-0.54)
Planning/Control	0.007*	0.013**	0.015**	0.011	0.019**
	(1.83)	(2.51)	(2.54)	(1.40)	(2.39)
AI Hardware	0.001	-0.003	-0.006	-0.006	-0.005
	(0.55)	(-0.75)	(-1.60)	(-1.28)	(-0.93)
Non-AI	0.011***	0.019***	0.020***	0.020***	0.021***
	(7.84)	(7.46)	(6.73)	(5.83)	(5.08)
Obs.	158,343	141,643	127,036	114,292	103,116
Panel E. Total Factor Productivity					
Machine Learning	0.001	-0.002	-0.000	0.006	-0.001
	(0.56)	(-0.51)	(-0.06)	(1.31)	(-0.14)
Evolutionary Computation	0.000	0.001	0.001	-0.002	-0.003
	(0.17)	(0.15)	(0.50)	(-0.69)	(-1.10)
Natural Language Processing	0.001	0.003	-0.001	0.006	0.000
	(0.18)	(0.74)	(-0.20)	(1.46)	(0.03)
Speech	0.001	-0.004	0.007**	0.003	0.009***
	(0.23)	(-1.17)	(2.12)	(1.05)	(3.22)
Vision	0.001	-0.000	-0.006*	-0.009***	-0.006*
	(0.25)	(-0.17)	(-1.92)	(-2.90)	(-1.91)
Knowledge Processing	0.005	0.002	0.013	0.006	0.006
	(1.18)	(0.29)	(1.62)	(0.85)	(0.73)
Planning/Control	0.002	0.015**	0.002	0.007	0.004
	(0.46)	(2.57)	(0.29)	(1.16)	(0.55)
AI Hardware	-0.006**	-0.012***	-0.012***	-0.013***	-0.008
	(-2.36)	(-3.44)	(-2.71)	(-2.74)	(-1.15)
Non-AI	0.016***	0.018***	0.006	0.004	0.006
	(5.90)	(5.40)	(0.75)	(0.75)	(1.30)
Obs.	104,552	92,760	83,183	74,787	67,413

Table A.8: Firm Growth — 21_{st} Century

This regression specifies the same way as Table 5 but with sample period being 2000 to 2016. Detailed variable definitions are provided in Appendix Table A.1.

			Panel A. Profits		
AI Pat.	0.007*	0.008	0.007	0.008	0.008
	(1.78)	(1.60)	(1.10)	(1.01)	(0.85)
Non-AI	0.027***	0.037***	0.054***	0.062***	0.073***
	(6.09)	(4.27)	(4.74)	(4.39)	(4.20)
Obs.	62,378	57,319	52,954	49,138	43,228
			Panel B. Sales		
AI Pat.	0.001	0.002	0.004	0.008	0.011
	(0.20)	(0.53)	(0.74)	(1.12)	(1.26)
Non-AI	0.025***	0.039***	0.049***	0.054***	0.062***
	(5.44)	(5.28)	(4.79)	(5.36)	(4.73)
Obs.	62,378	57,319	52,954	49,138	43,228
			Panel C. Capital		
AI Pat.	0.006***	0.012***	0.017***	0.020***	0.027***
	(2.90)	(3.09)	(2.94)	(2.82)	(3.04)
Non-AI	0.016***	0.026***	0.038***	0.043***	0.047***
	(7.16)	(5.95)	(6.53)	(5.95)	(5.14)
Obs.	62,378	57,319	52,954	49,138	43,228
			Panel D. Employment		
AI Pat.	0.003*	0.007**	0.012***	0.016***	0.023***
	(1.77)	(2.48)	(2.89)	(2.86)	(3.31)
Non-AI	0.014***	0.020***	0.022***	0.023***	0.020**
	(6.49)	(5.30)	(4.17)	(3.51)	(2.41)
Obs.	62,378	57,319	52,954	49,138	43,228
			Panel E. Total Factor Productivity		
AI Pat.	0.000	0.003	0.003	0.005	0.003
	(0.05)	(0.87)	(0.54)	(0.91)	(0.54)
Non-AI	0.025***	0.023***	0.031***	0.033***	0.034***
	(7.33)	(4.46)	(5.15)	(4.86)	(4.28)
Obs.	42,607	38,899	35,939	33,306	29,417

Table A.9: Financing Regressions

This table shows the second-stage results for our 2SLS analysis. The dependent variables are various financing-related variables. The sample period is 2001 to 2016. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. Detailed variable definitions are provided in Appendix Table A.1. All potentially unbounded variables are winsorised at 1% level.

Panel A - 2SLS for AI patents

	Equity Issue	Debt Issue	Dividends/AT	Repurchase/AT
	(1)	(2)	(3)	(4)
θ^{AI}	-0.013	-0.018	0.001	0.028
	(-0.64)	(-1.61)	(0.93)	(0.20)
N(AI Applications)	0.006	0.006	-0.001	-0.036
	(0.64)	(1.17)	(-1.16)	(-0.55)
Ln(Assets)	0.016***	0.050***	-0.004***	-1.921***
	(4.47)	(16.42)	(-8.99)	(-21.29)
Ln(Firm Age)	-0.141***	0.010***	-0.002***	0.127***
	(-23.05)	(2.76)	(-4.07)	(2.72)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Obs.	55,096	55,096	54,966	55,096
R^2	0.03	0.01	0.01	0.25

Panel B - 2SLS for non-AI patents

	Equity Issue	Debt Issue	Dividends/AT	Repurchase/AT
	(1)	(2)	(3)	(4)
θ^{non-AI}	0.150	-0.026	0.000	-1.045
	(1.64)	(-0.47)	(0.01)	(-0.93)
N(Non-AI Applications)	-0.033**	0.004	-0.000	0.284
	(-2.22)	(0.43)	(-0.13)	(1.55)
Ln(Assets)	0.021***	0.050***	-0.004***	-1.938***
	(4.55)	(14.77)	(-8.05)	(-19.14)
Ln(Firm Age)	-0.141***	0.011***	-0.002***	0.138***
	(-23.22)	(2.95)	(-4.17)	(2.95)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Obs.	55,096	55,096	54,966	55,096
R^2	0.03	0.01	0.01	0.24

Table A.10: Firm Related Regressions — OLS

This table presents OLS regression results for firm investment and outcome. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. All potentially unbounded variables are winsorised at 1% level. Detailed variable definitions are provided in Appendix Table A.1. The sample period is 2001 to 2016.

Panel A - Investment

	XRD/AT	CAPX/AT	Vert. Integ.	d2vscope	New TM	Acquirer	Target
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
θ^{AI}	0.001	0.001***	-0.000	0.070	0.022***	-0.001	-0.004***
	(0.73)	(3.96)	(-0.05)	(1.38)	(3.64)	(-0.27)	(-3.93)
N(AI Applications)	0.002***	-0.000	-0.003	-0.027	-0.003	-0.001	-0.002***
	(2.66)	(-0.38)	(-0.90)	(-0.78)	(-0.64)	(-0.86)	(-2.63)
Ln(Assets)	-0.035***	-0.001	0.051***	0.852***	0.088***	0.035***	-0.001
	(-22.93)	(-1.45)	(6.97)	(11.70)	(13.63)	(16.23)	(-0.81)
Ln(Firm Age)	0.005***	-0.005***	0.035***	0.170*	0.009	0.004*	0.013***
	(4.15)	(-6.38)	(2.96)	(1.94)	(0.84)	(1.69)	(7.87)
Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Obs.	55,096	55,096	54,577	51,594	55,096	55,096	55,096
R^2	0.84	0.68	0.86	0.78	0.74	0.18	0.20

Panel B - Outcome

	Total Q	OI/AT	VOL
	(1)	(2)	(3)
θ^{AI}	0.225***	0.001	0.450**
	(9.25)	(0.46)	(2.33)
N(AI Applications)	-0.097***	-0.002	-0.196
	(-5.93)	(-1.13)	(-1.06)
Ln(Assets)	0.169***	0.087***	-5.066***
	(5.67)	(21.64)	(-16.68)
Ln(Firm Age)	-0.702***	-0.000	-3.420***
	(-16.76)	(-0.00)	(-9.27)
Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Obs.	54,784	55,095	54,696
R^2	0.56	0.74	0.61

Panel C - Financing

	Equity Issue	Debt Issue	Dividends/AT	Repurchase/AT
	(1)	(2)	(3)	(4)
θ^{AI}	0.002	-0.004*	0.000	-0.082***
	(0.58)	(-1.83)	(0.05)	(-3.10)
N(AI Applications)	-0.000	0.000	-0.000	0.014
	(-0.15)	(0.01)	(-0.93)	(0.52)
Ln(Assets)	0.017***	0.050***	-0.004***	-1.927***
	(4.96)	(16.95)	(-9.23)	(-21.48)
Ln(Firm Age)	-0.140***	0.011***	-0.002***	0.124***
	(-23.14)	(2.87)	(-4.16)	(2.68)
Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Obs.	55,096	55,096	54,966	55,096
R^2	0.31	0.33	0.44	0.85

Table A.11: Industry Outcomes

This table presents the relationship between AI patent intensity and industry-level outcomes. We use NAICS 5-digits to define industries. The analysis is conducted at the industry-year level.

$$Y_{I,t+\tau} = \beta_0 + \beta_1 \frac{\text{AI Pat.}_{I,t}}{\text{All Pat.}_{I,t}} + \delta X_{I,t} + \alpha_I + \delta_t + \epsilon_{I,t+\tau}$$

We control for ln(Sales), ln(Employment), and ln(Total Patents) filed in year t. Industry and year fixed effects are included in all regressions. T-statistics adjusted for clustered standard errors at the industry level are reported in parentheses. ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively.Detailed variable definitions are provided in Appendix Table A.1. All potentially unbounded variables are winsorized at the 1% level. The sample period is from 1988 to 2016.

	t+1	t+2	t+3	t+4	t+5
			Panel A - Ln(Sales)		
AI Pat./All Pat.	0.025	0.032	0.075	0.175**	0.281***
	(0.82)	(0.58)	(1.01)	(2.18)	(2.82)
Obs.	6,429	6,221	5,997	5,752	5,498
			Panel B - Ln(Employment)		
AI Pat./All Pat.	0.081**	0.104*	0.146*	0.235**	0.341***
	(2.29)	(1.68)	(1.80)	(2.58)	(3.17)
Obs.	6,429	6,221	5,997	5,752	5,498
			Panel C - HHI (All firms)		
AI Pat./All Pat.	-0.010	-0.007	-0.010	-0.017	-0.016
	(-0.49)	(-0.31)	(-0.41)	(-0.78)	(-0.74)
Obs.	6,429	6,221	5,997	5,752	5,498
			Panel D - HHI (AI firms)		
AI Pat./All Pat.	-0.042*	-0.028	-0.014	-0.023	-0.038
	(-1.73)	(-1.16)	(-0.48)	(-0.77)	(-1.19)
Obs.	4,089	3,964	3,827	3,673	3,516
			Panel E - HHI (non-AI firms)		
AI Pat./All Pat.	-0.004	-0.008	-0.017	-0.026	-0.027
	(-0.17)	(-0.35)	(-0.68)	(-1.24)	(-1.32)
Obs.	6,423	6,214	5,989	5,742	5,489

Table A.12: AI patents and AI investment

This table presents the results on the relationship between AI patents and AI investment measured using job posting and resume data from Babina et al. (2024). T-statistics adjusted for clustered standard errors at the firm level are reported in parentheses. ***, **, * indicates significance level at 1%, 5% and 10%. Detailed variable definitions are provided in Appendix Table A.1. All potentially unbounded variables are winsorized at the 1% level. The sample period is 2010 to 2018.

	I(AI)			
	(1)	(2)	(3)	(4)
Share of AI workers (BurningGlass)	13.625***		-0.130	
	(5.93)		(-0.09)	
Share of AI workers (Cognism)		9.910***		2.073
		(3.59)		(1.34)
Ln(Assets)	0.033***	0.034***	0.029***	0.019***
	(9.13)	(11.86)	(3.45)	(3.41)
Tobin's Q	0.021***	0.018***	0.005*	0.004
	(5.71)	(6.25)	(1.76)	(1.35)
PPE	-0.081**	-0.068**	-0.085**	-0.042
	(-2.34)	(-2.57)	(-2.04)	(-1.33)
Non-AI Patents	0.005***	0.005***	0.004***	0.004***
	(25.07)	(29.45)	(8.03)	(9.35)
Year FE	✓	✓	✓	✓
SIC4 FE	✓	✓		
Firm FE			✓	✓
Obs.	13,796	23,742	13,467	23,070
R^2	0.44	0.43	0.74	0.72