

Displacement or Augmentation? The Effects of AI on Workforce Dynamics and Firm Value

Mark A. Chen¹, Joanna Wang²

August 2024

Abstract

This paper studies the effects of Artificial Intelligence (AI) innovation on firm-level employment dynamics and corporate valuation. Applying state-of-the-art deep learning and large language models (LLMs) to U.S. patent data during 2007-2023, we categorize AI-related innovations and find clear evidence of both labor augmentation and labor displacement effects. These AI-induced effects mainly occur through external hiring and growth in pre-existing job roles. Furthermore, augmenting AI innovations lead to higher firm values, especially in the presence of better worker protections and greater local labor mobility. Overall, our findings suggest that AI technology generally complements firms' workforces and enhances value.

JEL Classification Codes: G30, G32, O32, O33

Keywords: Artificial Intelligence (AI), firm innovation, patents, labor augmentation, labor displacement, large language models (LLMs), firm valuation

* The authors are grateful to discussants and participants at the Columbia & RFS AI in Finance Conference and the DEFT Academy/Xueshuo Summer Institute in Digital Finance for providing valuable feedback.

¹Corresponding author. J. Mack Robinson College of Business, Georgia State University, Atlanta, GA 30303, USA. Email: machen@gsu.edu; Tel.: 404-413-7339.

² PHBS Business School, Peking University, Shenzhen, 518055, China.

1. Introduction

The rapid development of artificial intelligence (AI) technologies over the past few years has led to growing interest among academics, practitioners, and policymakers in understanding the possible effects of systems that can process vast amounts of information, generate predictions and original content, and engage with human users. Many view AI technologies as a key driver of future economic growth (Aghion et al., 2017; Agrawal et al., 2019a; Furman and Seamans, 2019), with a large part of the gains coming from AI’s ability to complement and augment the productivity of knowledge workers.¹ At the same time, questions have arisen about the implications of AI technology for the labor market. As increasingly powerful AI systems begin to perform cognitive tasks that have traditionally been within the domain of skilled human labor, concerns have grown that widespread use of AI may lead to the displacement of skilled knowledge workers (Frey and Osborne, 2017), who have traditionally been considered as the beneficiaries of the spread of older automation technologies.²

Does AI technology complement human workers in cognitive tasks, thereby augmenting workforce productivity and creating new jobs and new demand for skilled labor? Or is it the case that AI can perform workplace tasks more inexpensively and more efficiently than humans can, leading to skill obsolescence, labor displacement, and higher unemployment in the future? Despite the obvious economic and public-policy importance of such questions, they have been difficult to address due to a lack of large-scale evidence on AI innovation and workforce dynamics (Seamans and Raj, 2018). In this paper, we use textual data from millions of patents over 2007-2023 and

¹ See e.g. Goldman Sachs (2023), which estimates that advances in AI, such as ChatGPT and other generative AI systems, can complement most knowledge workers’ jobs and potentially lead to a 7% rise in global GDP over a 10-year period. Academic studies that highlight AI’s ability to complement and improve workers’ performance include, for example, Brynjolfsson et al. (2018), Ernst et al. (2019), Webb (2019), and Lane and Saint-Martin (2021).

² Reflecting such concerns, the U.S. President’s Executive Order issued October 30, 2023 cited disruptions to the workforce caused by job displacement as one of the key potential risks posed by AI (United States, 2023).

microdata on worker flows to provide some of the first causal evidence on how AI innovation impacts firm-level employment and value.

As a general-purpose technology (GPT), AI includes a remarkably broad range of components, functionalities, and real-world applications (Brynjolfsson and McAfee, 2017; Caliskan and Lum, 2024). Thus, empirically studying the effects of AI is challenging because different types of AI technology may have markedly different effects on firms and labor markets. To address this practical challenge, we propose a new approach to studying AI in terms of its functional capabilities. Specifically, we employ textual data from millions of U.S. patents over 2007-2023 to identify AI technologies in areas that correspond to key aspects of human intelligence. We apply state-of-the-art techniques related to deep learning, semantic similarity search, Large Language Models (LLMs), and generative AI to categorize AI innovations into five overlapping functional areas: perception, inference, prediction, creativity, and engagement.³

We document a number of novel facts about the growth of AI innovation across functional areas, technological areas, and industrial sectors. For instance, we find that AI patenting in the U.S. as a fraction of all patenting has grown extremely rapidly over the past decade, increasing from about one percent in 2014 to about seven percent in 2023. Although the largest source of the more than 40,000 AI innovations in our sample is firms in the Transport, Storage, and Communications industries, a substantial amount of AI innovation also occurs across a broad range of other industries, including Manufacturing, Electricity, Social and Personal Services, and Wholesale and Retail Trade. The most common types of AI innovation in our sample are engagement-based AI and prediction-based AI, with more than 50 percent of all AI patents falling within each of these categories in most years. Inference-based AI is the single fastest-growing category: patenting in

³ Section 2 discusses the rationale for this categorization and provides definitions and examples for each category.

that category increased from 10% to more than 40% of all AI patenting over the sample period, likely reflecting the tremendous growth in data analysis and machine-learning algorithms.

In the main part of our analysis, we examine whether the different categories of AI innovation have effects on innovating firms' workforce dynamics. For this purpose, we use a new dataset that details the employment of individual workers and their job transitions to, from, and within firms in our sample. These data, which are obtained from Revelio Labs, cover essentially all employees at U.S. publicly-traded firms (including their subsidiaries) from 2008 to the present. In addition to detailing worker movements at a monthly frequency, the dataset also has information on employees' education levels and specific within-firm roles, enabling us to construct measures of skill and to observe firm-level employment changes with respect to both existing job roles and entirely new roles.

In studying the link between AI innovation and firm-level employment, one important issue that arises is potential endogeneity: observed relations between innovation and employment could reflect non-causal correlations arising from the influence of other factors. For example, AI patenting activity might be correlated with changes in labor markets, industries, consumer demand, or corporate policies (e.g., overall patenting or R&D spending) that are the true drivers of changes in firms' labor-market strategies. To address these concerns, we follow the approach of prior work that uses the quasi-random assignment of patent applications to patent examiners within different U.S. Patent and Trademark Office (USPTO) art units (Gaule, 2018; Sampat and Williams, 2019). Given that some patent examiners are more lenient than others, the quasi-random assignment of patent applications induces variation in the probability that a firm successfully obtains, for example, a certain number of AI patent grants within a certain category.⁴ Using this approach, we construct

⁴ Some other papers that use quasi-random assignment of patent applications to capture exogenous variation in patent grants include Farre-Mensa et al. (2020), Melero et al. (2020), and Yang and Yuan (2022).

instrumental variables that enable us to capture exogenous variation in firm-level patent flows within each of our five different AI categories.

We document evidence that AI innovations have both augmenting and displacing effects with respect to skilled labor. In particular, perception-based innovations and engagement-based innovations significantly increase innovating firms' use of skilled labor, whereas inference-based innovations significantly decrease it. These results are robust to instrumental variables (two-stage least squares) regression analysis as well as to the use of firm fixed effects, fixed effects for year-by-application count totals for different types of AI, and time-varying controls for R&D spending, firm size, and recent operating performance. Additional results show that the augmentation effect appears to be driven by an increased inflow of skilled workers from external labor markets rather than by internal reskilling of workers or by a reduction in skilled-worker job separations. This pattern suggests that firms often choose to leverage new AI technologies with new workforce talent acquired from outside hiring despite the well-known labor-adjustment costs associated with searching for, recruiting, and training new workers.

Examining further the nature of skilled-labor augmentation, we find that most of the AI-induced growth in skilled labor takes the form of “core augmentation,” i.e., labor growth in pre-existing roles within the firm. However, there is little evidence that AI innovation drives “scope augmentation,” which we define as hiring or appointing employees to entirely new roles. This contrast in findings supports the idea that many AI innovations increase the demand for skilled labor by complementing workers in their pre-existing roles rather than helping workers to expand into entirely new roles.

While the focus of our analysis is on skilled labor, which *a priori* is the segment of the workforce most likely to be affected by AI's ability to perform cognitive tasks, we also examine

the impact of AI innovation on unskilled labor growth. A stylized fact that emerges from prior research is that automation can result in skill-biased technical change (Acemoglu, 2002), whereby increased productivity of skilled workers shifts firms' labor demand towards newer products or processes and away from modes of production that rely heavily on less-skilled labor. Interestingly, we find that the AI innovation categories that augment skilled labor (i.e., perception and engagement) have either positive or insignificant effects on unskilled labor growth, while the AI category that displaces skilled labor (inference) also displaces unskilled labor. Thus, based on our evidence, it does not appear that skilled-labor augmenting AI innovations represent an overt form of skill-biased technical change.

Next, to study the firm-value effects of augmenting or displacing AI innovation, we classify each patent as augmenting or displacing according to the empirically estimated effects of that patent's category on skilled labor growth. We use regression analysis to explore the effects of these types of AI innovation on innovators' Tobin's Q. A priori, there are several reasons to expect that both augmenting and displacing AI patents can yield value to innovators. For instance, new AI tools that enhance the productivity of existing workers in a firm (Ersahin, 2020; Yang, 2022) could prompt the firm to scale up production by hiring more workers of the same type. Alternatively, an AI innovation could create value by fostering entirely new jobs (Bessen, 2018; Badet, 2021) or tasks (Acemoglu and Restrepo, 2018) that themselves require additional hiring or reskilling of workers with the firm. AI could also lead to increased firm growth and product innovation (Babina et al., 2024). In the case of labor-displacing AI, a firm could potentially reap large cost savings by laying off human workers and substituting for them with automated AI that is equally capable, but less expensive (Hussey, 2003; Seamans and Raj, 2018).

We find evidence that augmenting AI patents generally have a positive effect on firm value as measured by Tobin's Q. In OLS regressions and instrumental variables regressions that control for firm fixed effects and year-by-application-count fixed effects for different patent types, we find that the quantity of augmenting patents in a firm-year has a significant, positive effect on firm value. In contrast, displacing patents (as well as patents that are neither augmenting nor displacing) have insignificant effects on Tobin's Q. Moreover, the difference in the value effect between augmenting patents and displacing patents is statistically significant. Taken together, these findings suggest that firms can benefit most from AI innovations that augment skilled labor rather than displacing it.

What explains the significant value premium of augmenting patents relative to displacing patents? We conjecture that augmenting patents contribute more to firm value because such patents, unlike displacing patents, do not lead to heightened unemployment risk or larger labor-adjustment costs, both of which are ultimately borne by the firm. To examine this conjecture, we estimate regressions of firm value on augmenting and displacing AI innovation using subsamples based on cross-sectional differences in state laws and labor market frictions. We find that when firms face greater external hiring costs as measured by higher state-level enforceability of noncompete clauses or a smaller number of local rivals, the positive value impact of augmenting AI innovations disappears. Additionally, augmenting AI patents increase firm value only when the innovator is headquartered in a state that has not passed a Right-to-Work labor law or that features a relatively high amount of unemployment insurance coverage. In other words, the value gains associated with augmenting AI patents materialize only when, from the standpoint of the innovating firm, there is good mobility and availability of skilled workers in the external labor market.

Our paper contributes to several strands of literature, including research in finance and economics pertaining to AI innovation, firm-level employment, and the application of text analytics. First, we add to a stream of papers that study the adoption of AI technology and its consequences for certain occupations. Aghion et al. (2017) and Agrawal et al. (2019b) provide a conceptual framework for the effects of AI on job task displacement and augmentation. Some empirical studies examine the effects of AI and big data technologies on financial analysts (Grennan and Michaely, 2020; Cao et al., 2024; Abis and Veldkamp, 2024) and the effects of robo-advisors on financial advisors and asset management (Rossi and Utkus, 2021; Kumar, 2023).

Our work is also directly related to recent papers that explore the implications of AI technologies for firm growth and employment. Specifically, Babina et al. (2024) find that AI-investing firms experience higher employment growth and market valuations through increased product innovation. Eisfeldt et al. (2024) find that firms with high exposure to generative AI (i.e., the public release of ChatGPT) experience less frequent hiring and higher stock returns on account of labor-technology substitution.⁵ To date, however, researchers have not distinguished among different types of AI innovations to test for heterogeneous effects on employment dynamics. By using individual-level employment data, patent text data, and large language model techniques, we are able to identify and categorize individual AI patents into five functional areas. Our functional approach to studying the impact of different types of patents enables us to more precisely examine how firm-level employment and value respond to the arrival of new AI technologies.

⁵ Alderucci et al. (2020) also document a positive association between AI-related inventions and employment growth. In contrast, Huang et al. (2023) find that freelancers in various occupations experience reductions in both employment and earnings after the mainstream arrival of generative AI. In another recent paper, Acemoglu et al. (2022b) find that employers who adopt AI simultaneously reduce hiring in non-AI positions and alter the skill requirements of remaining postings.

Third, our paper contributes to the literature that examines the broad economic implications of automation, skill-biased technological innovation, and creative destruction. Several existing papers focus on the consequences of automation technologies, narrowly defined. For instance, researchers have used the stock of industrial robots in different industries and countries (Acemoglu and Restrepo, 2020; Bates et al., 2021; Qiu et al., 2021) as a proxy for the extent of physical automation. Some recent studies emphasize that technological innovation may create new jobs and reinforce labor growth (Acemoglu and Restrepo, 2019; Autor and Salomons, 2018). Other papers discuss the skilled-biased feature of technological innovation (Autor et al., 2003; Acemoglu and Autor, 2011) which affects high and low-skilled labor in different ways. Griliches (1969) and Krusell et al. (2000) argue that equipment and information technology (IT) capital are more complementary to skilled labor than to unskilled labor. To study the effects of AI, Kogan et al. (2023) develop measures of labor-saving and labor-augmenting technology. Motivated by such work, our paper focuses on AI, widely considered to be one of the broadest and most impactful general-purpose technologies to have emerged in recent years, which may be a key driver of the growing demand for skilled labor. However, rather than pre-defining labor-augmentation (displacing) technologies, we take an agnostic approach to which specific types of AI innovations are truly augmenting (displacing) for skilled and unskilled labor. Thus, we can obtain a much more complete picture of the varied scope of AI technologies and their consequences for firm-level labor dynamics.

Finally, our work offers a new methodological approach to the study of large-sample textual data that can potentially be applied to many other questions in finance and economics. A large and growing literature in financial economics uses Natural Language Processing (NLP) techniques to study corporate filings, disclosures, patent texts, and other textual data. Earlier

studies in this area use text-filtering or word-embedding algorithms that are easier to interpret, but less accurate (Loughran and McDonald, 2011; Henry and Leone, 2016; Routledge, Sacchetto, and Smith, 2013; Webb, 2019). Later studies exploit techniques related to machine-learning and generative AI (Chen et al., 2019; Giczy et al., 2022; Li et al., 2024, Jha et al., 2024) to analyze textual data. We build on these recent approaches by combining state-of-the-art techniques in large language modeling and Retrieval Augmented Generation (RAG). As one of the first papers in financial economics to construct and employ an RAG system, we are able to classify AI innovations at scale with less ambiguity and subjectivity than would be possible with traditional text filtering or with a generative LLM alone. Our novel approach performs well in classifying individual out-of-sample patent applications, thus enabling us to separately identify the causal effects of AI innovation in different functional categories.

2. Identifying Functional Categories of AI

While there is no single, universally accepted definition of AI, a view commonly held by researchers and practitioners is that AI consists of computing systems that can accomplish tasks and functions that have traditionally required human intelligence. The idea that artificial intelligence can or should do what human intelligence is capable of has featured prominently in the work of computer scientists since at least the mid-20th century. For example, in 1950 Alan Turing proposed a test based on an “imitation game” whereby a computer can be said to possess artificial intelligence if it can adequately mimic human responses under certain conditions. (Turing, 1950). In 1956, John McCarthy, often described as the “Father of AI,” organized a summer conference that is widely regarded as the birth of AI as a scientific field. The conference proposed to study machines based on the conjecture that “every aspect of learning or any other feature of

[human] intelligence can in principle be so precisely described that a machine can be made to simulate it.”

In the decades since the founding of the AI field, major technical advances such as artificial neural networks, deep learning, and generative AI have enabled artificial systems to equal or exceed human performance in specific, narrowly-defined cognitive tasks. Many computer scientists and engineers believe that progress will eventually lead to Artificial General Intelligence (AGI), which is a form of machine intelligence that would be able to think, reason, create, and generally behave across different domains like human intelligence without the need for extensive pre-training. At the current time, AGI remains only a hypothetical possibility since even state-of-the-art AI systems require pre-training and do not generalize readily across different fields. Nonetheless, the development of intelligent systems that can fully match humans across the broad range of their cognitive tasks persists as one of the central goals of research in the field.⁶

Motivated by the oft-discussed parallels between AI and human intelligence, we propose to categorize and study AI innovations according to which of their capabilities resemble key aspects of human cognition. Our categorization of AI is based on five (overlapping) functional areas, namely, perception, inference, prediction, creativity, and engagement. These categories can be described as follows:

- ***Perception***: Gathering, organizing, and identifying sensory information from external stimuli to gain an awareness of the environment
- ***Inference***: Drawing conclusions based on evidence and/or logical reasoning

⁶ For example, as stated by Yann LeCun, Turing Award winner and Chief AI Scientist at Meta, “We want to build intelligent machines that learn like animals and humans.” (LeCun, 2022).

- **Prediction:** Indicating or foretelling outcomes based on observation, experience, or scientific reason
- **Creativity:** Transcending traditional ideas, rules, patterns, or relationships to generate new ideas, forms, methods, interpretations, or possibilities
- **Engagement:** Understanding, interacting with, and responding to the behavior of human users

Table 1 provides, for each functional category, some specific tasks/capabilities and examples of AI technology that can be associated with that category. The above categorization is not exclusive—individual technologies can be associated with more than one category. As an example of this, using a generative AI tool such as ChatGPT could be regarded as AI engagement because of its interaction with human users, but at the same time it may involve predictions and creativity based on user input. Furthermore, although the categories collectively span all or almost all AI-related technologies, they do not include all dimensions of AI. For example, the ability to learn is a property of the vast majority of AI systems, but we do not use it as a categorizing dimension because it is not useful for studying important differences between different AI types. Finally, it should be noted that, with respect to particular AI inventions, the categories are intended to capture the degree to which technologies function as part of the intended AI system. For instance, an improved design for a generic microprocessor would not be considered an AI innovation or technology even though one of the possible uses of the microprocessor is as a hardware component of an AI system.

3. Data

3.1 Sample

Our source of data on firms' AI innovation is the full-text database of patent applications and grants at the USPTO Bulk Data Storage System (BDSS)⁷. From the PatentsView website⁸, we obtain information on individual patents' citations and their International Patent Classification (IPC) codes. To identify the patenting activities of U.S. public firms, we proceed to merge together the USPTO data with CRSP/Compustat. We start by building links within the USPTO data between patent applications and patent grants. From Jan 2007 to December 2023, there are 5,913,659 utility patent applications, and 3,765,176 of them are observed to have been granted. Next, from the data sample⁹ of Kogan et al. (2017), henceforth, KPSS, we obtain the linking data between USPTO patent grant numbers and CRSP PERMNO (PERMCO) identifiers. (This sample covers 3,160,453 patents from 1926 to 2022). To identify the patent application information up to 2022, we retrieve the internal link between grants and applications from USPTO and match it with the KPSS data. Among patents for which both application and grant information are available, we have 1,014,772 patents filed by CRSP U.S. firms from the KPSS data.

The previous step does not include (1) patent applications that were not yet (never) granted from 2000 to 2022; (2) patent applications that were not yet (never) granted in 2023; and (3) patent grants in 2023. Thus, we use a basic name-matching algorithm to supplement the linking between CRSP firms and USPTO patents. From the KPSS data, we use PERMNO (PERMCO) identifiers to retrieve all relevant firms' historical names from the CRSP database. For patent grants, we

⁷ <https://bulkdata.uspto.gov/>

⁸ www.patentsview.org

⁹ This dataset provides an updated data series for KPSS (Kogan, et al., 2017) values and forward citations, a patent number to the CRSP "PERMNO" match, and a patent number-to-CPC class match following the paper.

directly downloaded the assignee data from the Patents View database.¹⁰ We then extract patent assignee (applicant) information for all applications from the USPTO bulk database.¹¹ Using the name mapping between granted patent assignee and CRSP firm historic names, we further identify 961,655 patent applications before 2022 as well as 45,123 patent applications and 21,132 grants in 2023.¹² Finally, we obtain other firm-level data from the CRSP/Compustat merged database. The resulting sample consists of 2,307 unique U.S. firms that file 1,562,529 patent applications from 2007-2023, of which 1,253,239 are granted by the end of 2023.

3.2 Identifying and categorizing AI patents with LLM and generative AI methods

Until very recently, the standard approach in finance and economics for analyzing textual data has been to use text filtering or word embedding techniques to classify documents according to single-word frequencies or the co-occurrence of certain pairs of words.¹³ However, while such methods are straightforward and easy to interpret, they do not make full use of the semantic connections between words, sentences, and documents that can dramatically improve document search, filtering, and classification. The recent development of generative AI tools such as ChatGPT and Google Gemini has made it possible to retrieve documents and data sources using simple queries that refer to general topics or concepts. These instances of Large Language Models (LLMs) are trained on trillions of tokens and can respond to queries using a large set of commonsense knowledge. For example, a user could request ChatGPT to give a definition of

¹⁰ The Patents View database (<https://patentsview.org/download/data-download-tables>) only provides assignee information for granted patents.

¹¹ For patent applications, we cleaned and parsed the USPTO patent application XML files and extracted patent assignee names if they were recognized as organizations.

¹² Specifically, these additional patents are identified when their assignee names can be found in the KPSS matched pairs between CRSP firm names and USPTO assignee names.

¹³ Papers that use such techniques, include, for example, Tetlock et al. (2008), Hanley and Hoberg (2010), Loughran and McDonald (2011), Jegadeesh and Wu (2013), Hoberg and Phillips (2016), and Li et al. (2021).

“artificial intelligence” or to return a list of recent research papers in computer science that pertain to AI systems.

While generative AI models can provide intuitive responses to specific queries, such models face two basic limitations for our purposes. First, publicly available LLMs are not pre-trained on the large set of millions of patent filings filed with the USPTO. Hence, such models by themselves will not be able to retrieve a comprehensive list of AI patents from among the totality of patent filings. Second, LLMs currently have context window length limits (e.g., 8,192 tokens or words) that restrict the amount of input text a user can provide in a single query.

In view of these limitations, we turn to a recently developed NLP technique, Retrieval Augmented Generation (RAG), which combines different components of machine-learning systems together to enhance the effectiveness of querying an LLM (Lewis et al., 2020). The main idea behind the RAG technique is that part or all of the text in an initial query to an LLM can be used to rapidly retrieve (through vector similarity search) a small amount of highly relevant text from a large collection of documents previously stored in a vector database. The retrieved text can then be added as contextual background to the initial query, forming a single prompt that leads to a more informed and more accurate response from the LLM. To our best knowledge, we are the first in the finance and economics field to use an RAG system for identifying and classifying different types of patents.¹⁴

Our overall approach to identifying AI innovations from among the millions of U.S. patent applications filed during 2007-2023 consists of two main steps. First, we build a custom RAG system and use it to construct a training sample of labeled patents for each of the five AI categories. Second, we use the data thus labeled to train downstream machine-learning classifiers that can

¹⁴ Li et al. (2024) is the only other paper in financial economics we are aware of that uses an RAG system to analyze a large collection of textual documents (analyst research reports).

categorize all patent applications in the entire sample. For ease of exposition, we only summarize these two steps here and defer more detailed descriptions to Appendix B.

To assemble our RAG system, we combine two open-source model components: (1) a pretrained, semantic embedding model for mapping patent filing texts into a high-dimensional vector space; and (2) a state-of-the-art, open-source LLM for handling the augmented queries.¹⁵ Using the semantic embedding model, we convert the abstract text of each patent application in the overall sample (about 5 million patent filings) into a 768-dimensional numerical vector. We then formulate key retrieval phrases that reflect the concepts underlying our five AI categories. For example, the retrieval phrase for perception-based AI is “artificial intelligence that has perception ability.” Upon converting the retrieval phrases themselves into vector embeddings with the semantic embedding model, we use cosine similarities to identify and retrieve patent abstracts that have high semantic similarity to the retrieval phrases. Random sampling from among these retrieved samples yields five training samples (one for each AI category), each consisting of 1,700 patent applications.

For each training-sample patent application, we submit a query to the LLM to ascertain whether the application belongs to the relevant category. Queries take the form of a specific yes/no question followed by the actual patent abstract text. Thus, for instance, to check whether a application in the training sample is related to perception-based AI, we query the LLM with the prompt “*Is the following invention related to artificial intelligence that has perception ability? Respond with YES or NO and give an explanation. [followed by the patent abstract text]*”. The

¹⁵ The semantic embedding model used is *sentence-transformers/all-mpnet-base-v2*. The primary LLM that we use is Microsoft Corp.’s *Phi-3-8k-Small-Instruct* model, which was released in May 2024 under an open-source license (MIT) permitting broad commercial and research use. This model is available at <https://huggingface.co/microsoft/Phi-3-small-8k-instruct>. As of July 2024, *Phi-3-8k-Small-Instruct* is the highest-performing 7-billion parameter open-source LLM, outperforming 2023 versions of GPT 3.5 Turbo and GPT 4 according to key LLM performance benchmarks.

LLM yes/no responses form binary labels for the training data.

To ensure that our RAG approach is able to correctly distinguish different types of patents with a high degree of reliability, we check various responses given by the LLM. Appendix A provides examples, for each AI category, of both positive and negative classifications from the LLM. Based on our review of these examples and numerous others, we conclude that the LLM is capable of differentiating between fine shades of meaning in patent abstracts. For instance, consider the case of Patent Application # 20200242402, “Method and Apparatus for Recognizing Object,” (Samsung Electronics Co., LTD), listed in Appendix A. Despite the fact that the abstract for this patent filing does not contain the term “perception” or any other synonymous terms, the LLM correctly recognizes that the patent invention demonstrates AI and visual perception ability because the disclosed system can extract and correlate feature information in images. Also, we note that the LLM is able to reliably determine when an invention is not directly AI-related. For example, the LLM correctly recognizes that Patent Application # 20220155785, filed by May Mobility Inc. is not perception-based AI (see Appendix A). As explained by the LLM, although this invention does involve collecting and processing data from onboard sensors, the focus of the invention is on selecting policies for autonomous decision-making rather than on perception ability itself.

We then use the labeled training data to train five downstream logistic regression models for the purpose of categorizing all patent applications. For these models, only the 768 elements of the semantic embedding vectors are included as explanatory covariates. In other words, the classifier models do not depend on any features apart from those related to the patent abstract texts. Once the models are trained, we apply them to the entire sample (approximately five million patent applications) to generate out-of-sample predicted probabilities of whether or not patents belong to

each of the five categories of AI. We use a cutoff level of 0.75 to convert the fitted probabilities to predicted binary outcomes.

3.3 Firm employment data from Revelio Labs

We obtain data on U.S. firm-level employment from a novel database compiled by Revelio Labs. The Revelio database is constructed using unstructured online public profiles, resumes, and job postings from both LinkedIn postings and company websites. The database aggregates global workforce dynamics of public employer and employee records from more than 4.5 million companies and 1.1 billion resume profiles, allowing us to see current and historical workforce composition and firm-level trends. Compared to other datasets (e.g., Compustat) that provide only very limited information about the distribution of employment across a firm's subsidiaries, the Revelio data provide us with parent-subsidiary relationships, enabling us to match our company list to the Revelio company universe and other public data.¹⁶ Revelio Labs also collects and provides data on employers' job postings, employee sentiment, and layoff events.¹⁷ At the firm level, the Revelio workforce dynamics data provide us with a novel distribution of labor outcomes in each role. Specifically, the data include monthly headcounts, inflows, outflows, and wage-by-worker characteristics, such as a job role taxonomy with clustering at different levels of granularity.¹⁸ At the individual employee level, the data provide information on demographics (e.g.,

¹⁶ Some studies use administrative data from the Census Bureau Research Data Centers (RDCs) to obtain information on employment at the employee-establishment level. However, the overall data coverage depends on which states approve the relevant data application. Thus, incompleteness in the data (due to a state's non-approval) may substantially limit the study of employee transitions across states.

¹⁷ The history begins in 2008 for company website postings and in August 2021 for LinkedIn job postings.

¹⁸ The job role taxonomy is clustered by mathematical representations of each job using the title, the text description of the position (from either individual describing their own experiences or employers on a job posting), and individuals' skills, associates, and previous experience. The role taxonomy is adjusted periodically to adapt to the changing occupational landscape.

name, gender, race, origin), job position (affiliated firm identify, title, job category, salary, tenure), skill taxonomy, education, and job transition.¹⁹

There are two key advantages of using this novel dataset in our study of AI effects on firm employment. First, the within-firm inflow and outflow records allow us to precisely identify technological effects on firm workforce dynamics. Given that different AI technologies may have concurrent augmenting and displacing effects, studying only the net growth in employment might lead to the spurious conclusion that workflows are unaffected by AI innovations. Likewise, the individual transition records also help us differentiate between labor upskilling (de-skilling) within the firm and labor augmentation from external hiring. Second, the Revelio Labs workforce dynamics data allow us to unpack the creative destruction of a firm’s labor composition across different roles. Prior studies use occupation-level data (e.g., the O*NET database) to study firms’ labor demand based on the skill requirements of each occupation. However, without individual-level details, one cannot obtain a full picture of firm-level workforce composition.²⁰ In contrast, the Revelio Labs data cover each employee’s job status and education history, which enables identification of the firm-level distribution of skilled labor within distinct job roles over time.

3.4 Variable construction

To examine how firm-level employment responds to AI technology adoption, we construct a set of outcome variables using the Revelio Labs data and financial information from Compustat. We first identify skilled labor for each firm from the distribution of educated workers in each role.

¹⁹ Specifically, the job transitions data give us a full picture of an employee’s work history, current status, and job transfers within or across firms over time. The transition data also allow us to track detailed information on characteristics of new (previous) firms and new (previous) jobs, including geographic location, firm identity, role name, salary, and job start (end) date.

²⁰ For instance, Ghaly et al. (2017) construct an industry-specific labor skill index (LSI) based on Occupational Employment Statistics (OES) data from the Bureau of Labor Statistics (BLS) and the O*NET program classification of occupations according to skill level.

Specifically, employees in a role with more than 25% educated workers in a given year are deemed to be skilled workers. Using the headcounts, inflow, and outflow of skilled and unskilled workers, we separately calculate the yearly *Skilled-labor Growth* and *Unskilled-labor Growth* at the firm level. To unpack the sources of net changes in skilled employment from hiring and (or) firing activities, we decompose the skilled-labor growth rate into the yearly growth rate of skilled workers that are internally re-allocated (*Skilled-labor reskilling*), the yearly growth rate of skilled workers that are externally hired (*Skilled-labor external hiring*), and yearly growth rate of skilled workers that departed from the firm (*Skilled-labor job separation*). To investigate whether AI innovation triggers labor adjustment in a firm’s core business or whether instead it increases the firm’s scope by creating new jobs, we track each firm’s job role distribution history and identify new job roles created in each firm year. We define *Skilled-labor core augmentation* as the percentage growth in skilled employees in existing roles. Similarly, we define *Skilled-labor scope augmentation* as the percentage growth of skilled employees in firm new roles. We define a job role as being new to a firm if it does not show up in the firm’s employment history before the most recent three years.

To test firm-level employment effects, we count the number of patents in each AI functional category based on our classification from the RAG and machine-learning classifier system. In later tests, we study the effects of AI innovation on firm value and label AI patents in each category based on their predicted employment outcomes. Specifically, we construct the *Log # of skilled-labor augmenting AI patents* as the log-transformed total number of patent grants in AI categories that are estimated to increase a firm’s skilled labor growth (see Table 4). Similarly, we construct the *Log # of skilled-labor displacing AI patents* as the log-transformed total number of patent grants in AI categories that are estimated to be displacing for skilled labor. The details are reported

in Section 4.3.1. Last, we construct a measure of firm value using the average Tobin's Q value for the two years after the year of patent filings. Following previous literature (Fazzari et al., 1988; Erickson and Whited, 2012), we calculate firm-year level Tobin's Q as the ratio of the book value of debt (Compustat items $DLTT + DLC$) plus the market value of equity (Compustat items $PRCC_F \times CSHO$) minus the firm's current assets (Compustat item ACT) to the book value of property, plant, and equipment (Compustat item $PPEGT$). All details of the construction of key variables are reported in Table 3 and Section 4.

3.5 Summary statistics

We first report the time-series distribution of AI patent applications in each category from 2007 to 2023. The AI patents are identified and grouped from the RAG system and machine learning classification as described in Section 2 and Appendix B. The five AI categories include perception-based AI, inference-based AI, prediction-based AI, creativity-based AI, and engagement-based AI. Figure 1 Panel A illustrates the distribution of AI patents as a fraction of all patents over time. We find an increasing trend of AI patenting activities from less than 1 percent to about 7 percent in the last two decades. The share of AI innovation dropped in the year 2021, possibly due to firms' financial stress during the Covid-19 pandemic (Ellul et al., 2020). From 2022 to 2023, AI innovation exhibits a significant upward spike, likely reflecting the mainstream arrival of generative AI (e.g., the public release of Chat-GPT in November 2022). Figure 2, Panel B illustrates the distribution of AI patents by functional category as a fraction of all AI patents over time. The evidence suggests that engagement and prediction account for a majority of AI innovations during this period (more than 50% in most years). Further, inference-, creativity-, and perception-based AI patents experienced positive growth in the most recent decade. Specifically,

the fraction of inference-based AI patents increased from 10% to more than 40% of all AI innovations, which is perhaps explained by the rapid development and applications of data analysis algorithms.

In Figure 2, we report the distribution of AI innovation activity by firm size, labor intensity, and R&D intensity. Panel A reports, by firm size, the firm-level AI patents in each category as a fraction of all of a firm's patents. In fact, small firms allocate more innovation resources to AI technologies than large firms do, although (according to untabulated statistics) large firms are more innovative in terms of total patent volume. The shares of perception- and engagement-based AI patents filed by small firms are about two times that of patents filed by large firms. Panel B summarizes AI patent shares in labor-intensive and capital-intensive (non-labor-intensive) firms. We find that, compared to capital-intensive firms, labor-intensive firms file relatively more inference-, creativity-, and engagement-based AI patents but fewer perception-based AI patents. In addition, the share of prediction-based AI patents is comparable in the two groups, suggesting that firms' investment in perception-based AI technologies is not sensitive to their existing labor share. Panel C provides comparisons of AI innovation in R&D-intensive and non-R&D-intensive firms. The figure shows that AI patents generally account for a larger fraction of all patents in R&D-intensive firms. The evidence suggests that AI innovation relies fundamentally on R&D as an input into the innovation process.

Table 2, Panels A and B separately report the summary statistics of AI patent applications and grants across different industrial sectors. Industrial sectors that experienced the most frequent AI innovation include communication (19,195 AI patent applications), manufacturing (16,448 AI patent applications), and electricity (3,309 AI patent applications). The innovators in the communication and electricity sectors consist of a large number of high-tech firms. In addition,

firms in retail, mining, and service industries (likely to be labor-intensive firms) also have a sizable AI innovation especially for prediction- and engagement-based AI patents. Panels C and D report the distribution of AI patent applications and grants in the five most frequent technology classes based on patent IPC classification. All five categories of patents heavily build on technologies related to Computing, Calculating, Counting (G04); Electric Communication Technique (H04) and Musical Instruments and Acoustics (G10)²¹. Prediction-based AI innovation also derives fundamentally from underlying technologies in Controlling and Regulation (G05) and Measuring and Testing (G01).

In Appendix C, Table C1, we report the patent-level characteristics in each of the five categories of AI patents and non-AI patents. We construct four variables to proxy for patent quality: forward citations, IPC breadth, originality, and generality. The IPC breadth measure indicates the scope of technologies that an invention embodies. Forward citations are a standard measure in the literature that capture the contribution of patents in terms of impact and influence on future patents. Following Hall et al. (2001) and Hsu et al. (2014), we further construct patent originality and generality measures to capture forward and backward measures of technology scope. Last, we estimate the dollar value of a patent following Kogan et al. (2017).²² All detailed definitions are reported in Table B3. As shown in the table, perception-based AI patents have the highest breadth (1.66) as measured by the unique number of 3-digit IPC classes. For both applications and grants, creativity-based AI patents receive more forward citations and higher value than other AI patent

²¹ The Musical Instrument and Acoustics (G10) technology class is not only restricted to musical instruments. It includes technologies applied on sound emitting devices. For example, some artificial intelligence patents on methods or devices for transmitting, conducting, or directing audios can be classified under this category. See more details in https://www.wipo.int/ipc/itos4ipc/ITSupport_and_download_area/20240101/pdf/scheme/full_ipc/en/g10.pdf

²² Specifically, we calculate a KPSS (Kogan et al., 2017) value for each patent grant, $KPSS\ value = (1 - \underline{\pi})^{-1} \frac{1}{N_j} E[v_j | R_j] M_j$, where $\underline{\pi}$, the unconditional probability of successful patent application; N_j is the number of patent applications a firm filed on the same day; and M_j is the firm's market capitalization five trading days prior to the application announcement date t .

categories. Importantly, the market valuation of non-AI patents is lower for both applications (29.95.24 billion in USD) and grants (40.91 billion in USD) than any category of AI patents. The positive differences in patent quality between AI and non-AI patents are also present in patent citations, generality, and originality.

Next, we report the characteristics of firm innovation and employment outcomes in Table 3. Panel A reports the sample distribution of patent applications and grants for the various AI categories. The firm-level yearly average number of perception-based AI patents is 0.18 for applications and 0.11 for grants. Prediction-based AI patents are, on average, more frequently observed within a firm year (1.13 for applications and 0.69 for grants). Panel A also reports the frequency of firms' skilled-labor augmenting and displacing AI patents, which are defined based on estimated firm employment effects (e.g., higher skilled-labor growth) in the year after the patent filings.²³ The average number of AI patent grants that lead to skilled-labor augmentation (displacement) is 0.89 (0.43) for each firm in a given year.

Panel B reports firms' yearly employment and financial characteristics. The average skilled-labor yearly growth rate is 8.3%, with a 4.3% growth rate explained by new employment in firm existing job roles. The internal reskilling growth rate is 5.7% which is significantly lower than the growth rate of external hirings (20.1%). The yearly average job separation is -18%, suggesting a high employee turnover rate. Unskilled employment share on average experiences a decrease of 7% on a yearly basis. All other variable definitions for firms' financial information are reported in Table 3.

4. Empirical Results

²³ A detailed description of how we reclassify patents is given in Section 4.3.1.

In this section, we describe the details of our empirical approach, including our basic identification strategy, the construction of instrumental variables, the model specification for two-stage analysis, and our method of labeling AI patents based on the estimated employment effects of the different AI patent categories. We then report our empirical findings.

4.1 Identification

To identify the causal effects of AI patent grants on firm-level outcomes, we exploit exogenous variation in patent approval rates that arises from the randomness in how patent applications are allocated to examiners at the U.S. Patent and Trademark Office (USPTO). This approach to identification, which is due to Gaule (2018) and Sampat and Williams (2019),²⁴ exploit two key institutional features of the USPTO patent examination process. First, individual patent examiners are observed to differ in terms of their leniency, i.e., in how likely they are to allow a patent application into granted status. Second, although patent applications are sent to different art units (groups of examiners) based on technological attributes, the assignment of patent applications to individual examiners within an art group is largely random (Lemley and Sampat, 2012; Sampat and Williams, 2019).²⁵

We extend the approach of Gaule (2018) to construct instrumental variables that can account for two or more different types of patenting by a firm in a given year.²⁶ First, for each examiner k in each year t , we calculate a time-specific leniency measure, E_{kt} , as the fraction of

²⁴ See also Farre-Mensa et al. (2020), who use a related approach to study how winning a patent grant causally affects a startup’s employment and sales growth.

²⁵ Lemley and Sampat (2012) conduct written interviews with USPTO examiners about the patent assignment process. They find no evidence of selection based on characteristics of applications other than observed conditions in standard USPTO datasets (i.e., technology type represented by USPTO art unit).

²⁶ The analysis of Gaule (2018) only considers a firm’s total number of patent applications and does not distinguish among patent types. By partitioning a firm’s patent applications within a year into different groups, we are able to study how various types of AI patents causally affect firm-level outcomes.

applications the examiner reviewed during the year that were granted. Because an examiner's art unit could induce a systematic component to his or her leniency, we estimate a simple regression to account for year-specific art unit effects:

$$E_{kt} = \Gamma' \mu_{lt} + \epsilon_{kt}, \quad (1)$$

where μ_{lt} denotes art unit-by-year fixed effects. The residual from this regression, denoted by E_{kt}^* , constitutes an “adjusted” measure of examiner k 's leniency in year t that accounts for the overall leniency of the examiner's art unit in the same year. Then, for any given patent category of interest, we can define instruments for patenting activity within and outside of the category:

$$Z_{it,Type} = \frac{1}{n_{it,Type}} \sum_{j \in D_{it,Type}} E_{k(j,t),t}^* \quad (2)$$

$$Z_{it,NonType} = \frac{1}{n_{it,NonType}} \sum_{j \in D_{it,NonType}} E_{k(j,t),t}^* \quad (3)$$

In these instrument definitions, $D_{it,Type}$ ($D_{it,NonType}$) is the set of patent applications filed by firm i in year t within (outside of) the category of interest, and $n_{it,Type}$ ($n_{it,NonType}$) is the total number of applications during the year within (outside of) the category. $k(j, t)$ is the random examiner to which patent application j is assigned in year t . In essence, these two instruments partition a firm's total innovation activity in a year into two groups—within-category applications and out-of-category applications—and separately capture how “lucky” the firm is in randomly drawing lenient examiners for the two groups of applications.

With instruments $Z_{it,Type}$ and $Z_{it,NonType}$ constructed as above, we can estimate the causal effects of different types of innovation on firm-level outcomes. For example, to examine the effects of a firm's patenting within and outside of a particular AI category, we estimate two-stage least-squares (2SLS) models of the following form:

First stage:

$$TypePatents_{it} = \alpha_0 + \alpha_1 Z_{it,Type} + \alpha_2 Z_{it,NonType} + \alpha_3 X_{it} + \gamma_i + \delta_{kt} + \mu_{kt} + \varepsilon_{it} \quad (4)$$

$$NonTypePatents_{it} = \beta_0 + \beta_1 Z_{it,Type} + \beta_2 Z_{it,NonType} + \beta_3 X_{it} + \gamma_i + \delta_{kt} + \mu_{kt} + v_{it} \quad (5)$$

Second stage:

$$Y_{i,t+n} = \delta_0 + \delta_1 \widehat{TypePatents}_{it} + \delta_2 \widehat{NonTypePatents}_{it} + \delta_3 X_{it} + \gamma_i + \delta_{kt} + \mu_{kt} + u_{it} \quad (6)$$

In this two-stage model, $TypePatents_{it}$ is the log of one plus the number of granted within-category AI patents filed by firm i in year t , and $NonTypePatents_{it}$ is the log of one plus the number of all other granted patents filed by firm i in year t . $Y_{i,t+n}$ is a firm-level measure of employment or value; and X_{it} is a set of controls. The controls include firm size, firm performance, and R&D expenditures. The term γ_i captures firm fixed effects. The terms δ_{kt} and μ_{kt} capture fixed effects corresponding to Year \times (# of Type applications) and Year \times (# of Non-Type applications), respectively. (We include these year-by-count fixed effects to control for any remaining heterogeneity related to firms' total volumes of Type and Non-type patent applications per year.) Provided that our instruments are valid, the coefficient δ_1 in the second-stage equation will capture the causal firm-level effect of patent grants that lie within the AI category of interest.

4.2 How does AI innovation reshape firm labor composition?

4.2.1 The labor-augmenting and labor-displacing effects of AI innovation

Our empirical analysis starts with the effects of different AI technologies on skilled labor growth. New technologies may increase firm demand for skilled labor that can adapt to new production processes and operate advanced systems (Acemoglu and Restrepo, 2019; Autor and Salomons, 2018). On the other hand, some AI innovations may lead to technological unemployment for skilled labor due to the substitution effects (Frey and Osborne, 2017). The contrasting views could be explained by the fact that AI technologies have different functional capabilities which could affect skilled labor growth in opposite directions. For instance, the AI-based user interface implemented in the workplace can be used to collect and deliver information when interacting with employees. It may significantly increase the efficiency of existing workers without displacing any of their jobs. In addition, this technology can also increase firm demand for other skilled workers, such as technicians for data security and system maintenance. However, some other AI technologies, such as AI-based systems that rely on machine learning and natural language processing algorithms, may disrupt existing employees by replacing repetitive tasks of human beings. They can perform reasoning and inference functions just like data-centric workers but in a more efficient way.

To explore the labor effects of AI technologies based on their functional capabilities, we implement, for each of the five AI categories, the two-stage instrumental variable approach as described in Section 4.1. We measure firm-level AI innovations as the log-transformed number of patent grants in a particular AI category each year. The regression also includes the number of other patent applications filed by a firm during the year. The two variables are instrumented by separate measures of average patent examiner leniency for each type of AI patent application and

other patent applications filed by a firm during the year. The dependent variable in each regression, *Skilled-labor Growth*, is the firm-level net growth rate of skilled labor share in the year following AI patent applications. Skilled labor is defined as employees in roles that consist of more than 25% of educated workers with at least a bachelor's degree.

Table 4 reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm skilled-labor growth. For ease of exposition, we report the first-stage results in Appendix C Table C2. Both the first-stage regression results and F-statistics are significant, rejecting the weak instrument hypothesis. In Table 4, each regression includes firm fixed effects, the number of “type” AI and “other” patent applications by year fixed effects, and a set of firm characteristics as control variables. The significant positive coefficients on the *Log # of AI patents of type Perception* and *Log # of AI patents of type Engagement* in Columns (1) and (5) suggest that AI patents related to perception and engagement facilitate skilled labor augmentation. Specifically, a 1% increase in perception (engagement)-based AI patent will result in about a 0.39% (0.14%) increase in the skilled labor growth in the following year. The significant negative coefficients on *Log # of AI patents of Inference* in Column (2) suggest that AI innovation related to inference explains skilled labor displacement. A 1% increase in inference-based AI patent will result in over a 0.15% decrease in skilled labor growth in the following year. We find no significant effects of prediction- and creativity-related AI on skilled labor growth. Our results are consistent with the recent literature on both skill-technology complementarity and skill-technology substitution. The heterogeneous effects of different functions of AI technologies also help us provide additional perspective on the ongoing debate over how technology affects labor augmentation and displacement.

4.2.2 The reskilling, hiring, and job separation effects of AI innovation

To gain a deeper understanding of the skilled-labor employment changes around AI technology adoption, we decompose the net growth of skilled labor into three components: internal reskilling, external hiring, and job separation. Intuitively, the increase in skilled labor share could take place through an increase in new hires (internally or externally) and a decrease in job turnover. Each mechanism can help generate important implications for firms' labor adjustment policies on firing and hiring activities. Using the Revelio Labs job transition data, we measure firms' new hiring activities along two dimensions. First, we calculate the growth rate in the number of skilled workers who are promoted within the firm. Second, we calculate the growth rate in the number of skilled workers who are newly hired from outside of the firm. Then, we use the turnover flow of firms' existing employees as a measure of job separation for skilled labor. These three parts of employee flow jointly explain the net changes of skilled labor growth around AI innovation. To study AI innovation effects on skilled-labor growth through different channels, we re-use the 2SLS specification and replace the overall skilled-labor growth with three separate outcomes.

Table 5 reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm skilled-labor growth through reskilling (Panel A), external hiring (Panel B), and job separation (Panel C) in the year following AI patenting activities. The first-stage regression results are reported in Appendix C, Table C2. All other variables and instruments are from the previous test in Table 4. The dependent variable in Table 5 Panel A, *Skilled-labor reskilling*, is a firm's net growth in internal inflow for skilled labor. We find significant positive effects of perception-based AI on skilled labor internal reskilling, suggesting that perception-related AI technologies increase firms' skilled labor growth through internal promotions. In addition, the negative coefficients in Columns (2)-(3) indicate the displacement effects of inference- and

prediction-based AI on skilled labor through reduced internal hiring activities. The dependent variable in Panel B, *Skilled-labor external hiring*, is a firm's net growth in external skilled-labor inflows. Interestingly, all five categories of AI innovation significantly affect firms' external hiring of skilled workers, but in different ways. As shown in Columns (1), (4), and (5), perception-, creativity-, and engagement-based AI innovation significantly increases firms' external hiring. In contrast, we find that inference- and perception-based AI innovation negatively affect skilled-labor growth through external hiring in Columns (2)-(3).

In Panel C, *Skilled-labor job separation* is a firm's net change in skilled employee departures. Except for the weak positive effects of perception-based AI reported in Column (1), we find little evidence of skilled-labor displacement through job separation. Overall, the results in Table 5 indicate that AI innovation significantly affects firms hiring activities. The skilled-labor augmentation is mainly through external hiring, especially after creativity- and engagement-based AI innovation. The displacement effects can be largely explained by the decrease in internal and external hiring when firms adapt to inference- and perception-based AI innovation. The evidence on job separation suggests that AI-induced firing activities are less frequently observed than the other two types of labor adjustment policies.

4.2.3 Core and scope augmentation effects of AI innovation

Next, we discuss skilled labor augmentation on both the intensive and extensive margins. On one hand, core augmentation for skilled labor takes place when AI innovation complements workers' existing jobs (Autor et al., 2003; Acemoglu and Autor, 2011; Acemoglu et al., 2022b) and improves the firm's production function, thus helping the firm to expand its core business. On the other hand, labor augmentation could be scope augmentation when AI innovation enables firms to

create new jobs and explore new products and businesses (Cockburn et al., 2019; Babina et al., 2024). To tackle this question, we further decompose skilled labor augmentation into two outcomes. We define Core augmentation to be the net growth of skilled labor in existing job roles. Scope augmentation is measured as the net growth of skilled labor in the firm's new job roles.

Table 6 reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm skilled-labor growth through these two types of augmentation. As reported in Panel A, we find that perception- and engagement-based AI innovation significantly increase skilled-labor growth in firms' existing job roles, suggesting that these AI technologies increase product efficiency and help expand firms' core business. The results are also consistent with the results from baseline regressions on overall skilled-labor augmentation in Table 4. In Panel B, we find no significant effects of any AI technology on scope augmentation, indicating that AI innovation does not facilitate or prevent firms' exploitation of new business areas. In addition, AI innovation does not affect firms' resource allocation between core and non-core businesses. The evidence is consistent with the creative destruction literature which documents the human-complementarity of AI technology. Further, we provide additional results that convey the message that new jobs created by AI mainly contribute to firms' expansion of their existing businesses.

4.2.4 The effects of AI innovation on unskilled-labor growth

Previous tests document the effects of AI innovation on firm employment growth on skilled labor. In this section, we conduct tests to investigate whether AI technologies reshape the workforce composition with respect to unskilled labor share. The employment growth of unskilled labor could be directly and indirectly affected by the adoption of AI technologies. On one hand, AI innovations can directly increase (through within-firm upskilling and external hiring) or

decrease (through firing) firm demand for unskilled labor. On the other hand, AI technology adoption may involve indirect effects on unskilled labor. Prior literature suggests that skill-biased technology could induce displacement effects which in some cases concurrent with labor enforcement effects (Berman et al., 1998). Firms with optimal labor capacity could rationally shift from unskilled labor to skilled labor in order to adopt skill-biased technologies. In this case, implementing skilled labor augmentation may force firms to cut down unskilled labor for cost-saving purposes. Alternatively, when AI innovations displace skilled labor, firms can replace unskilled workers with technology-disrupted skilled workers, thus causing an indirect displacement effect on unskilled labor.

Table 7 reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm unskilled-labor growth. The dependent variable, *Unskilled-labor growth*, is a firm's net growth in unskilled labor in the year following AI innovation. Unskilled labor is defined as employees in roles that have less than 25 percent of workers who are educated with at least a bachelor's degree. As shown in Column (2), the significantly negative coefficients on inference-based AI patents suggest displacement effects on unskilled labor. A 1% increase in inference-based AI patent grants results in a 9 basis points decrease in unskilled labor growth. Consistent with the previous discussion, the displacement effects can be explained by within-firm human capital resource re-allocation through internal employment down-skilling. In Column (5), we find that engagement-based AI patents have significant positive effects on unskilled labor growth. The results confirm the direct effects of unskilled-labor augmentation and reject the view that firms shift resources to adapt AI innovation by cutting down the share of expenses represented by unskilled labor costs. Lastly, we find no significant effects of perception-, prediction-, and creativity-based AI on unskilled labor, which suggests that (1) unskilled workers are not exposed

to tasks related to these technologies or (2) the effects of these technologies on skilled works have no spillovers to unskilled workers. Jointly, the results in Table 7 confirm the view that AI innovation, although different from automation, still has both augmentation and displacement effects on unskilled labor growth.

4.3 AI innovation and firm value

Our previous findings suggest that AI innovation significantly impacts firm employment dynamics by both augmenting and displacing skilled labor. Since skilled-labor augmentation and displacement may involve different cost-benefit tradeoffs, they can have different implications on firm efficiency. To gain more insights, this section further explores the value consequences of AI innovations that augment or displace skilled labor. To pin down the two channels, we explore the heterogeneity of AI technologies by re-classifying AI patents into larger groupings based on their predicted effects on firms' employment outcomes. We expect the skilled-labor augmentation and displacement may have different effects on firm value. If adopting AI technologies increases skilled-labor growth in firms' core business, firm value can increase due to production growth and improved efficiency. In the other case of skilled-labor growth decrease by AI technologies, firm value can either increase due to labor cost-saving or decrease due to sizeable firing costs.

4.3.1 Labeling patents based on firm employment effects.

To study the effects of AI innovation on firm value, we re-classify all AI patents into skilled-labor augmenting AI patents and skilled-labor displacing AI patents based on predicted firm employment outcomes. Specifically, we identify whether patents in each AI category filed by a firm in year t are predicted to increase or decrease the firm's skilled labor growth in the year after

AI adoption. Based on the regression results in Table 4, we define all perception- and engagement-based AI patents as skilled-labor augmenting patents and all inference-based AI patents as skilled-labor displacing patents. Then, we re-construct instruments for each type of patent using a similar approach to the one described in Section 4.1.

4.3.2 *The effects of AI patents on firm value*

Using the labeled patents and re-constructed instruments, we repeat the IV-2SLS analysis in previous tests and study the value effects of different AI innovations. We examine firm value changes resulting from skilled-labor augmenting patents and skilled-labor displacing patents. We construct the measure *Log # of skilled-labor augmenting AI patents* as the log-transformed total number of patent grants that are predicted to augment a firm's skilled labor (i.e., perception- and engagement-based AI patents). Then, we define the *Log # of skilled-labor non-augmenting AI patents* as patents in inference, prediction, and creativity categories. Similarly, the *Log # of skilled-labor displacing AI patents* is the log-transformed total number of patent grants that are predicted to be displacing skilled labor (i.e., inference-based AI patents). All the rest of the patents in other AI categories are counted in *Log # of skilled-labor non-displacing AI patents*. The instruments include the average patent examiner leniency for the firm's filed AI patent applications of a particular type during the year and the average patent examiner leniency for the firm's other patent applications filed during the year. Since we are interested in the subsequent outcomes of firm value after AI adoption in year t and real changes in labor adjustment in year $t+1$, we measure firm value as the average Tobin's Q over the two years (i.e., $t+1$ and $t+2$) following AI innovation.

Table 8 reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm value. The first-stage regression results are reported in Appendix C Table C3.

As shown in Column (1), skilled-labor augmenting AI patents results in a significant increase in Tobin's Q. Specifically, a 1% increase in skilled-labor augmenting AI innovation is associated with a 0.28 unit increase in Tobin's Q (2% increase relative to the sample mean). The results are consistent with the discussion that AI innovations, in the case of augmenting skilled labor, facilitate firm growth and create value. In Column (2), we find no significant effects of skilled-labor displacing patents on firm value. In Columns (1) and (2), the difference (a)-(b) is the difference in coefficients on *Log # of "type" AI* and *Log # of "other" AI*. Column (3) reports the results of pooled regression which have both skilled-labor augmenting and displacing patent variables. We measure *the Log # of augmenting/displacing AI patents* as the log-transformed total number of patent grants that are not predicted to be augmenting or displacing for skilled labor. The difference (a)-(b) is the difference in coefficients on the *Log # of Skilled-labor augmenting AI* and *Log # of Skilled-labor displacing AI*. The F-statistic for tests of difference in Column (3) suggests that the value effects of augmenting AI patents are significantly more positive than displacing AI patents for skilled labor. Overall, we find that AI innovations that facilitate skilled labor growth can increase firm efficiency, whereas skilled-labor displacing AI innovation does not. The difference in the value effects between the two types of AI patents is also statistically significant.

4.3.3 Heterogeneity of AI innovation effects on firm value

As discussed in the last section, AI innovation can increase firm value through changes in labor composition because new technology improves the firm's growth by augmenting skilled employees who are potentially more productive. The results in Table 5 suggest that AI innovations have substantial effects on firms' external hiring activities. Thus, the potential value effects of AI-induced labor adjustment can vary with the environment of the external labor market. In other

words, skilled-labor augmenting (displacing) AI innovations can be more value-creating when firms have lower costs associated with external hiring and firing activities. In this section, we investigate the value differentials across firms that are subject to high and low labor adjustment costs.

To understand whether the effects of AI innovation vary with labor market frictions, we focus on firms' heterogeneity in their exposure to (1) labor market competition with business rivals and (2) state-level regulations on labor protections. We use two measures of labor market competition that firms may face when interacting with their rivals. First, we use the state-level enforceability index of non-compete clauses (NCC) from Garmaise (2011). Prior studies have documented that the increase in non-compete enforceability can restrict labor mobility and induce firm labor costs, especially for knowledge-intensive occupations (Starr et al. 2021; Jeffers, 2024). Therefore, we use non-compete enforceability to capture the ease with which firms can hire employees from rivals and the potential costs of losing their employees (and trade secrets) to rivals. Second, we use the number of local rivals as a proxy for labor-market depth. Firms located in states with low (high) NCC enforceability index and more (fewer) rivals may find it easier (harder) to attract new employees from firms and more (less) costly to retain employees and prevent these employees from being poached by rival firms.

Table 9 reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm value in subsamples. Columns (1) and (2) report the results in subsamples of firms with headquarters located in *High NCC* (non-compete enforceability index is above the sample median each year) and *Low NCC* states (non-compete enforceability index the sample median each year). Columns (3) and (4) report the results in subsamples of firms with *More rivals* (above the sample median each year) and *Fewer rivals* (below the sample median each year) within

the same state. The rivals of a given firm (or subsidiary) are calculated as the average number of non-focal in-state employees. Any subsidiary-level rivals (from the Revelio Lab database) are then aggregated to the parent firm level by taking the average across different states. Other variables of interest are from the previous test and are defined in Table 3. In Column (2), we find significant positive effects of skilled-labor augmenting AI patents and negative effects of skilled-labor displacing AI patents on firm value, compared to insignificant effects of both in Column (1). As reported in Column (3), we find significant positive effects of skilled-labor augmenting AI patents and negative effects of skilled-labor displacing AI patents on firm value, compared to the results in Column (4). Specifically, augmenting (displacing) AI innovation increases (decreases) firm value when firms are located in states with low NCC enforceability and more rivals. Difference (a)-(b) in all regression is in coefficients on *Log # of Skilled-labor augmenting AI* and *Log # of Skilled-labor displacing AI*. The F-statistics for tests of difference indicate statistical significance in Columns (2) and (3). The results in Table 9 are consistent with the prediction that augmenting (displacing) AI patents in firms that are subject to low hiring costs (high firing costs) creates more value.

Next, we introduce two state-level regulations on labor protection. First, we obtain state-level right-to-work (RTW) law data from National Conference of State Legislatures (NCSL)²⁷ and use it serves as a proxy for firms' exposure to hiring frictions. Intuitively, right-to-work law weakens union power and induces labor adjustment costs due to more bargaining power of firms relative to employees (Matsa, 2010; Chava et al., 2020). In this case, employees may be discouraged from joining the firms in RTW states that may ex-post extract rents from workers.

²⁷ The data source is from <https://www.ncsl.org/labor-and-employment/right-to-work-resources>.

Devos and Rahman (2018) also use the unemployment insurance data from the US Department of Labor to examine the effects of unemployment insurance on firms' cash holding.

Hence, one should expect firms in non-RTW states to be more attractive and have lower costs of hiring in external labor markets. Second, we use state-level unemployment insurance as a measure of labor adjustment costs. Employees in firms with less generous unemployment insurance benefits bear with high unemployment risks and demand a wage premium as compensation (Topel, 1984a). Labor-displacing AI innovation can amplify this unemployment risk, thus inducing more labor costs for the firm. The literature also finds that unemployment insurance benefits increase employees' tolerance for firm risks and reduce firm labor cost, which results in a higher job application rate and hiring rate (Acemoglu and Shimer, 1999; Van Doornik et al., 2022). Hence, we expect that firms located in states with high unemployment insurance benefits may be subject to lower hiring costs because the coming employees anticipate strong protections against unemployment in the future. By the same token, these firms may have lower firing costs since existing employees can be compensated by unemployment insurance in the case of displacement.

We report the subsample test results in Table 10. Columns (1) and (2) report the results in subsamples of firms with headquarters located in *RTW passed* (right-to-work law passed) states and *RTW not passed* (right-to-work law not yet or never passed) states. Columns (3) and (4) report the results in subsamples of firms with headquarters located in *High UI* (unemployment insurance benefits above the sample median each year) and *Low UI* (unemployment insurance benefits below the sample median each year). The state-level unemployment insurance data is obtained from the U.S. Department of Labor.²⁸ The unemployment insurance benefit is calculated as the product of average weekly benefits and reciprocity rates of the regular programs. Other variables of interest are from the previous test and are defined in Table 3. As reported in Column (2), the positive effects of skilled-labor augmenting AI patents on firm value in the *RTW passed* subsample. Similarly, we

²⁸ The data source is from <https://oui.doleta.gov/unemploy/data.asp>

find significant positive effects of skilled-labor augmenting AI patents on firm value in the *High UI* subsample. This further confirms that firms with lower hiring costs may create more value in adopting labor-augmenting technologies. In addition, we find significantly negative effects of skilled-labor displacing AI innovation on firm value in the *Low UI* subsample. This evidence indicates that firms with less labor protection may involve higher hiring costs (e.g., lawsuits) and lead to less value creation compared to firms with strong unemployment protection. The results in this section show that the effects of AI innovation on firm value can be affected by firms' exposure to both hiring and firing frictions in the labor market. Specifically, firms that are subject to low hiring costs (high firing costs) create more value after adopting labor-augmenting (displacing) technologies.

5. Conclusion

The rapid pace of innovation in the field of AI has led to growing interest among academics, practitioners, and policymakers in understanding the possible benefits and consequences of new computing systems that can process vast amounts of information, perform reasoning and prediction, generate novel content, and engage with human users. While increasingly powerful AI technologies offer the promise of improving firms' productivity within virtually every industrial sector, questions have arisen about the effects that AI will have on labor markets. Does AI tend to augment and complement human workers, thus creating new roles, new jobs, and new demand for skilled labor? Or will AI be able to match and surpass humans in cognitive workplace tasks, leading to skill obsolescence, labor displacement, and increased unemployment? These questions have been difficult to answer due to the lack of large-scale data on the various types of AI innovation and the impact that these innovations have on the movements of skilled and unskilled workers.

In this paper, we use over three million patent filing texts from 2007-2023 and microdata on workforce dynamics to study the labor-market and firm-value impact of AI innovations. To implement our study, we propose a new categorization of AI based on five functional areas that correspond to key aspects of human intelligence: perception, inference, prediction, creativity, and engagement. Using state-of-the-art techniques in Large Language Models (LLMs) and Generative AI to identify patents in these functional categories, we study the causal impact of each innovation type on worker flows and firm value. We document evidence of both augmentation and displacement: AI innovations related to perception or engagement significantly increase skilled labor growth, AI while innovations related to inference significantly reduce it. Skilled labor augmentation through AI innovation appears to mainly take the form of increased external hiring rather than reduced job separations or internal reskilling. We also find that augmentation concentrates in existing “core” roles within the firm rather than in entirely new roles, and it does not appear to represent skill-biased technological change.

While augmenting AI innovations generally translate into higher firm valuations, their exact value impact depends heavily on the labor market circumstances surrounding the innovating firm. We find, for example, that the positive value impact of labor-augmenting AI innovations disappears when firms face greater external hiring costs as measured by high enforceability of in-state non-compete provisions or fewer local rival firms. Moreover, augmenting AI innovation does not increase value when the innovator is headquartered in a state with Right-to-Work laws or with a low level of unemployment insurance coverage. Overall, these findings are consistent with the view that many AI innovations have favorable effects for both innovating firms and the skilled workforce, but these positive effects may fail to materialize when the costs of external hiring and labor adjustment are high.

References

- Abis, S., and Veldkamp, L. 2024. The changing economics of knowledge production. *The Review of Financial Studies* 37:89-118.
- Acemoglu, D. 2002. Technical change, inequality, and the labor market. *Journal of Economic Literature*, 40:7-72.
- Acemoglu, D., and Autor, D. 2011. Skills, tasks and technologies: Implications for employment and earnings. *Handbook of Labor Economics* 4:1043-1171.
- Acemoglu, D., and Restrepo, P. 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review* 108:1488-1542.
- Acemoglu, D., Restrepo, P. 2019. Automation and new tasks: how technology displaces and reinstates labor. *J. Econ. Perspect* 33:3–30.
- Acemoglu, D., and Restrepo, P. 2020. Robots and jobs: Evidence from U.S. labor markets. *Journal of Political Economy* 128:2188-2244.
- Acemoglu, D., and Shimer, R. 1999. Holdups and efficiency with search frictions. *International Economic Review* 40:827-849.
- Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. 2022b. Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics* 40: S293-S340.
- Aghion, P., Jones, B. F., and Jones, C. I. 2017. Artificial intelligence and economic growth (Vol. 23928). Cambridge, MA: *National Bureau of Economic Research*.
- Agrawal, A., Gans, J., and Goldfarb, A. 2019a. *The economics of artificial intelligence: an agenda*. Chicago, IL: University of Chicago Press.
- Agrawal, A., Gans, J. S., and Goldfarb, A. 2019b. Artificial intelligence: the ambiguous labor market impact of automating prediction. *Journal of Economic Perspectives* 33:31-50.
- Alderucci, D., Branstetter, L., Hovy, E., Runge, A., and Zolas, N. 2020. Quantifying the impact of AI on productivity and labor demand: Evidence from US census microdata. *In Allied social science associations—ASSA 2020 annual meeting*.
- Austin, D. H. 1993. An event-study approach to measuring innovative output: The case of biotechnology. *The American Economic Review* 83:253-258.
- Autor, D. H., Levy, F., and Murnane, R. J. 2003. The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics* 118:1279-1333.

Autor, D., and Salomons, A. 2018. Is automation labor-displacing? Productivity growth, employment, and the labor share. NBER Working Paper No. w24871.

Babina, T., Fedyk, A., He, A., and Hodson, J. 2023. *Firm investments in artificial intelligence technologies and changes in workforce composition*. National Bureau of Economic Research Vol. 31325.

Babina, T., Fedyk, A., He, A., and Hodson, J. 2024. Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics* 151:103745.

Badet, J. 2021. AI, automation and new jobs. *Open Journal of Business and Management* 9:2452-2463.

Bates, T. W., Du, F., and Wang, J. J. 2021. Workplace automation and corporate financial policy. Working Paper, Arizona State University.

Berman, E., Bound, J., and Machin, S. 1998. Implications of skill-biased technological change: international evidence. *The Quarterly Journal of Economics* 113:1245-1279.

Bessen, J. 2018. AI and jobs: The role of demand. NBER Working Paper No. w24235.

Brynjolfsson, E., and McAfee, A. 2017. The Business of Artificial Intelligence, *Harvard Business Review*, July 18, 2017.

Brynjolfsson, E., Mitchell, T., and Rock, D. 2018. What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings* 108:43-47.

Caliskan, A., and Lum, K. 2024. Effective AI regulation requires understanding General-Purpose AI. *Brookings Institution* January 2024.

Cao, S., Jiang, W., Wang, J. L., and Yang, B. 2024. From man vs. machine to man+ machine: The art and AI of stock analyses. *Journal of Financial Economics Forthcoming*.

Chava, S., Danis, A., and Hsu, A. 2020. The economic impact of right-to-work laws: Evidence from collective bargaining agreements and corporate policies. *Journal of Financial Economics* 137:451-469.

Chen, M. A., Wu, Q., and Yang, B. 2019. How valuable is FinTech innovation? *The Review of Financial Studies* 32:2062-2106.

Cockburn, I., Henderson, R. and Stern, S. 2019. The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis. *The Economics of Artificial Intelligence: An Agenda*. University of Chicago Press 115-148.

Devos, E., and Rahman, S. 2018. Labor unemployment insurance and firm cash holdings. *Journal of Corporate Finance*, 49, 15-31.

- Ellul, A., Erel, I., and Rajan, U. 2020. The COVID-19 pandemic crisis and corporate finance. *The Review of Corporate Finance Studies* 9:421-429.
- Erickson, T., and Whited, T. M. 2012. Treating measurement error in Tobin's q. *The Review of Financial Studies* 25:1286-1329.
- Eisfeldt, A. L., Schubert, G., Zhang, M. B., and Taska, B. 2024. The labor impact of generative AI on firm values. Working Paper, UCLA Anderson School of Management.
- Ernst, E., Merola, R., and Samaan, D. 2019. Economics of artificial intelligence: Implications for the future of work. *IZA Journal of Labor Policy* 9:1.
- Ersahin, N. 2020. Creditor rights, technology adoption, and productivity: Plant-level evidence. *The Review of Financial Studies* 33:5784-5820.
- Farre-Mensa, J., Hegde, D., and Ljungqvist, A. 2020. What is a patent worth? Evidence from the US patent "lottery". *The Journal of Finance* 75:639-682.
- Fazzari, S., Hubbard, R. G., and Petersen, B. 1988. Investment, financing decisions, and tax policy. *The American Economic Review* 78:200-205.
- Frey, C. B., and Osborne, M. A. 2017. The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114:254-280.
- Furman, J., and Seamans, R. 2019. AI and the Economy. *Innovation Policy and The Economy* 19:161-191.
- Garmaise, M. J. 2011. Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *The Journal of Law, Economics, & Organization*, 27:376-425.
- Gaule, P. 2018. Patents and the success of venture-capital backed startups: Using examiner assignment to estimate causal effects. *The Journal of Industrial Economics* 66:350-376.
- Ghaly, M., Anh Dang, V., and Stathopoulos, K. 2017. Cash holdings and labor heterogeneity: The role of skilled labor. *The Review of Financial Studies* 30:3636-3668.
- Giczy, A. V., Pairolo, N. A., and Toole, A. A. 2022. Identifying artificial intelligence (AI) invention: A novel AI patent dataset. *The Journal of Technology Transfer* 47:476-505.
- Grennan, J., and Michaely, R. 2020. Artificial intelligence and high-skilled work: Evidence from analysts. *Swiss Finance Institute Research Paper* 20-84.
- Griliches, Z. 1969. Capital-skill complementarity. *The Review of Economics and Statistics* 465-468.

- Hall, B. H., Jaffe, A. B., and Trajtenberg, M. 2001. The NBER patent citation data file: Lessons, insights and methodological tools. NBER Working Paper No. w8498.
- Hanley, K. W., and Hoberg, G. 2010. The information content of IPO prospectuses. *The Review of Financial Studies* 23:2821-2864.
- Henry, E., and Leone, A. J. 2016. Measuring qualitative information in capital markets research: Comparison of alternative methodologies to measure disclosure tone. *The Accounting Review* 91:153-178.
- Hoberg, G., and Phillips, G. 2016. Text-based network industries and endogenous product differentiation. *Journal of Political Economy* 124:1423-1465.
- Hsu, P. H., Tian, X., and Xu, Y. 2014. Financial development and innovation: Cross-country evidence. *Journal of Financial Economics* 112:116-135.
- Huang, Q., Shen, Y., Sun, Y., and Zhang, Q. 2023. The layoff generation: How generative AI will reshape employment and labor markets. Working Paper, The University of Illinois at Urbana-Champaign.
- Hussey, R. 2003. Labor turnover and the dynamics of labor productivity. Working Paper, Georgetown University.
- Jeffers, J. S. 2024. The impact of restricting labor mobility on corporate investment and entrepreneurship. *The Review of Financial Studies* 37:1-44.
- Jegadeesh, N., and Wu, D. 2013. Word power: A new approach for content analysis. *Journal of Financial Economics* 110:712-729.
- Jha, M., Qian, J., Weber, M., and Yang, B. 2024. ChatGPT and corporate policies. NBER Working Paper No. w32161.
- Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics* 132:665-712.
- Kogan, L., Papanikolaou, D., Schmidt, L. D., and Seegmiller, B. 2023. Technology and labor displacement: Evidence from linking patents with worker-level data. NBER Working Paper No. w31846.
- Krusell, P., Ohanian, L. E., Ríos-Rull, J. V., and Violante, G. L. 2000. Capital-skill complementarity and inequality: A macroeconomic analysis. *Econometrica* 68:1029-1053.
- Kumar, I. 2023. Impact of Robo-advisors on the Labor Market for Financial Advisors. Working Paper, Emory University.

- Lane, M., and Saint-Martin, A. (2021). The impact of Artificial Intelligence on the labour market: What do we know so far? *OECD Social, Employment and Migration Working Papers* No. 256
- LeCun, Y. 2022. A path towards autonomous machine intelligence version 0.9. 2, 2022-06-27. *Open Review* 62.
- Lemley, M. A., and Sampat, B. 2012. Examiner characteristics and patent office outcomes. *Review of Economics and Statistics*, 94:817-827.
- Lewis, P., Perez, E., Piktus, A., Petroni, F., Karpukhin, V., Goyal, N., et al. 2020. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems* 33:9459-9474.
- Li, K., Mai, F., Shen, R., and Yan, X. 2021. Measuring corporate culture using machine learning. *The Review of Financial Studies* 34:3265-3315.
- Li, K., Mai, F., Shen, R., Yang, C., and Zhang, T. 2024. Dissecting corporate culture using generative AI—Insights from analyst reports. Working Paper, University of British Columbia.
- Loughran, T., and McDonald, B. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance* 66:35-65.
- Matsa, D. A. 2010. Capital structure as a strategic variable: Evidence from collective bargaining. *The Journal of Finance* 65:1197-1232.
- McCarthy, J., Minsky, M. L., Rochester, N., and Shannon, C. E. 2006. A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI magazine* 27:12-12.
- Melero, E., Palomeras, N., and Wehrheim, D. 2020. The effect of patent protection on inventor mobility. *Management Science* 66:5485-5504.
- Pakes, A. 1985. On patents, R&D, and the stock market rate of return. *Journal of Political Economy* 93:390-409.
- Qiu, J., Wan, C., and Wang, Y. 2021. Labor-capital substitution and capital structure: Evidence from automation. Working Paper, McMaster University.
- Rossi, A. G., and Utkus, S. P. 2021. Who benefits from Robo-advising? Evidence from machine learning. Working Paper, Georgetown University.
- Routledge, B. R., Sacchetto, S., and Smith, N. A. 2013. Predicting merger targets and acquirers from text. Working Paper, Carnegie Mellon University.
- Sampat, B., and Williams, H. L. 2019. How do patents affect follow-on innovation? Evidence from the human genome. *American Economic Review* 109:203-236.

- Seamans, R., and Raj, M. 2018. AI, labor, productivity and the need for firm-level data. NBER Working Paper No. w24239.
- Starr, E. P., Prescott, J. J., and Bishara, N. D. 2021. Noncompete agreements in the US labor force. *The Journal of Law and Economics* 64:53-84.
- Tetlock, P. C., Saar-Tsechansky, M., and Macskassy, S. 2008. More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance* 63:1437-1467.
- Topel, R. H. 1984a. Equilibrium earnings, turnover, and unemployment: New evidence. *Journal of Labor Economics* 2:500-522.
- Turing, A. M. 1950. Computing machinery and intelligence. *Mind* 49:433-460.
- Van Doornik, B., Fazio, D., Schoenherr, D., and Skrastins, J. 2022. Unemployment insurance as a subsidy to risky firms. *The Review of Financial Studies* 35:5535-5595.
- Webb, M. 2019. The impact of artificial intelligence on the labor market. Working Paper, Stanford University.
- Yang, C. H. 2022. How artificial intelligence technology affects productivity and employment: firm-level evidence from Taiwan. *Research Policy* 51:104536.
- Yang, B., and Yuan, T. 2022. Trademark and IPO underpricing. *Financial Management* 51:271-296.

Appendix Index

Appendix A. Examples of LLM Responses to Queries About AI Patent Type

Appendix B. Using Retrieval-Augmented Generation (RAG) and Machine Learning to Identify Artificial Intelligence Patents

B.1 Construction of Labeled Training Data with RAG

B.2 Using the Labeled Training Sets to Classify all Patent Applications

Appendix C. Additional Tables

Table C1. Patent-Level Characteristics, by AI Category

Table C2. AI Innovation and Firm Employment: 2SLS First-stage Regressions
(For Tables 4-7)

Table C3. AI Innovation and Firm Value: 2SLS First-Stage Regressions
(For Table 8)

Appendix A. Examples of LLM Responses to Queries About AI Patent Type

Perception-based AI:

Title: METHOD AND APPARATUS FOR RECOGNIZING OBJECT

Patent Application Number: 20200242402

Patent Applicant/Assignee: Samsung Electronics Co., LTD.

Abstract: The present disclosure relates to an artificial intelligence (AI) system for simulating functions of a human brain such as cognition and decision-making by using machine learning algorithms such as deep learning, and applications thereof. In particular, the present disclosure provides a method of recognizing an object by using an AI system and its application, including: extracting pieces of first feature information respectively regarding a plurality of images, each image including an object; generating at least one piece of second feature information representing a correlation between the plurality of images by combining together the extracted pieces of first feature information respectively regarding the plurality of images; and recognizing, based on the at least one piece of second feature information, the object included in each of the plurality of images by using a pre-generated learning network model.

Explanation from LLM:

Yes, the invention is related to artificial intelligence that has perception ability. The explanation is that the AI system described is capable of recognizing objects in images by extracting and correlating feature information, which is a form of visual perception. The use of machine learning algorithms, such as deep learning, to simulate human brain functions like cognition and decision-making further supports the system's perception abilities.

Non-Perception-based AI:

Title: MULTI-PERSPECTIVE SYSTEM AND METHOD FOR BEHAVIORAL POLICY SELECTION BY AN AUTONOMOUS AGENT

Patent Application Number: 20220155785

Patent Applicant/Assignee: May Mobility Inc.

Abstract: A system and a method for autonomous decisioning and operation by an autonomous agent includes: collecting decisioning data including: collecting a first stream of data includes observation data obtained by onboard sensors of the autonomous agent, wherein each of the onboard sensors is physically arranged on the autonomous agent; collecting a second stream of data includes observation data obtained by offboard infrastructure devices, the offboard infrastructure devices being arranged geographically remote from and in an operating environment of the autonomous agent; implementing a decisioning data buffer that includes the first stream of data from the onboard sensors and the second stream of data from the offboard sensors; generating current state data; generating/estimating intent data for each of one or more agents within the operating environment of the autonomous agent; identifying a plurality of candidate behavioral policies; and selecting and executing at least one of the plurality of candidate behavioral policies.

Explanation from LLM:

NO, the described invention is not specifically related to artificial intelligence that has perception ability. While the system does involve collecting and processing data from onboard and offboard sensors, which is a part of perception, the focus of the invention is on autonomous decision-making and operation by an autonomous agent. The invention describes a method for integrating data from different sources, generating state and intent data, identifying candidate behavioral policies, and selecting and executing a policy. The key aspect of the invention is the decision-making process rather than the perception ability itself.

Inference-based AI:

Title: METHOD OF CONSTRUCTING THE INTELLIGENT COMPUTER SYSTEMS
BASED ON INFORMATION REASONING

Patent Application Number: 20110004582

Patent Applicant/Assignee: Nankai University

Abstract: A method of constructing the intelligent computer systems based on information reasoning, the method comprising the steps of: obtaining the problem from the users and analyzing the corresponding user demands; choosing the data relating to the user demands in databases and collecting the external data for solving the problems; preprocessing the data and generating the data tables; computing the field of probability on the basis of data tables; computing the degree of credibility of the information reasoning rule according to the new information theory; outputting the information reasoning rule if A, then B and its degree of credibility; storing the results of the discovered information reasoning rules. The intelligent computer systems constructed by this patent can extract information from the large amount of data automatically. The intelligent systems can decide whether A and B are positively related or negatively related to each other according to the degree of credibility of the information reasoning rule if A, then B, moreover, the degree of credibility shows the sufficient degree of the evidences in the reasoning. Since the present patent can help the users to obtain valuable information from the large amount of data, this method can be widely used to construct the intelligent systems based on the large amount of data.

Explanation from LLM:

Yes, the invention is related to artificial intelligence that has inference ability. The method described involves several steps that are characteristic of AI systems with inference capabilities: 1. Obtaining and analyzing user problems and demands: This step requires understanding natural language inputs, which is a task AI system, especially those with natural language processing (NLP) capabilities, are designed to perform. 2. Choosing and collecting relevant data: AI systems can automatically select and gather data from various sources, which is essential for making informed decisions. 3 Preprocessing data and generating data tables: Data preprocessing is a common task in AI to clean and organize data for further analysis. 4. Computing the field of probability: This involves statistical analysis and probabilistic reasoning, which are key components of many AI systems, particularly those that use Bayesian inference or other probabilistic models. 5. Computing the degree of credibility of information reasoning rules: This step requires the system to evaluate the strength of the relationships between different pieces of information, which is a form of logical

inference.6. Outputting the information reasoning rule and its degree of credibility: The system must be able to communicate its findings and the confidence it has in those findings, which is a critical aspect of AI systems that interact with humans.7. Storing the results of discovered information reasoning rules: This allows the system to learn from past inferences and improve its performance over time, which is a characteristic of machine learning, a subset of AI. Overall, the method described involves tasks that are well within the capabilities of AI systems with inference abilities, such as reasoning, learning, and decision-making based on data analysis.

Non-Inference-based AI:

Title: METHOD FOR UNDERSTANDING MACHINE-LEARNING DECISIONS BASED ON CAMERA DATA

Patent Application Number: 20180293464

Patent Applicant/Assignee: HRL Laboratories LLC.

Abstract: Described is a system for understanding machine-learning decisions. In an unsupervised learning phase, the system extracts, from input data, concepts represented by a machine-learning (ML) model in an unsupervised manner by clustering patterns of activity of latent variables of the concepts, where the latent variables are hidden variables of the ML model. The extracted concepts are organized into a concept network by learning functional semantics among the extracted concepts. In an operational phase, a subnetwork of the concept network is generated. Nodes of the subnetwork are displayed as a set of visual images that are annotated by weights and labels, and the ML model per the weights and labels.

Explanation from LLM:

No, the described invention is not directly related to artificial intelligence with inference ability. Instead, it is a system for understanding and interpreting machine-learning decisions by extracting concepts and organizing them into a concept network. The system does not perform inference itself but rather provides a way to visualize and comprehend the decisions made by an ML model.

Prediction-based AI:

Title: DATA ADAPTIVE PREDICTION FUNCTION BASED ON CANDIDATE PREDICTION FUNCTIONS

Patent Application Number: 20090210371

Patent Applicant/Assignee: University of California

Abstract: In one embodiment, a method for predicting an outcome is provided. The method comprises: determining a known data set of data, the known data set of data including an input variable and an output variable; determining a plurality of candidate prediction functions, each prediction function adapted to determine a candidate predicted outcome for the output variable using a different algorithm; determining a combination of the plurality of candidate prediction functions based on the known data set; determining a second set of data, the second set of data including data for the input variable; and determining, based on the input variable, a predicted

outcome for the output variable using a data adaptive prediction function, wherein the data adaptive prediction function uses the combination of candidate predicted outcomes from the plurality of candidate prediction functions determined using the data from the input variable to determine the predicted outcome.

Explanation from LLM:

YES, the invention is related to artificial intelligence that has prediction ability. The method described involves using a data set to determine multiple candidate prediction functions, each based on different algorithms, and then combining these functions to create a data adaptive prediction function. This adaptive function is then used to predict outcomes based on new input data. The process of selecting and combining different algorithms to predict outcomes is a common approach in machine learning, a subset of artificial intelligence focused on prediction and pattern recognition.

Non-Prediction-based AI:

Title: TRAINING DATA PROTECTION FOR ARTIFICIAL INTELLIGENCE MODEL IN PARTITIONED EXECUTION ENVIRONMENT

Patent Application Number: 20220414223

Patent Applicant/Assignee: EMC IP Holding Company LLC.

Abstract: Techniques for training data protection in an artificial intelligence model execution environment are disclosed. For example, a method comprises executing a first partition of an artificial intelligence model within a secure execution area of an information processing system and a second partition of the artificial intelligence model within a non-secure execution area of the information processing system, wherein data at least one of obtained and processed in the first partition of the artificial intelligence model is inaccessible to the second partition of the artificial intelligence model. Communication between the first partition and the second partition may be enabled via a model parallelism-based procedure. Data obtained in the secure execution area may comprise one or more data samples in an encrypted form usable to train the artificial intelligence model.

Explanation from LLM:

NO, the described invention is not directly related to artificial intelligence with prediction ability. Instead, it focuses on techniques for training data protection in an AI model execution environment. The invention aims to ensure data privacy and security by separating the execution of different parts of an AI model into secure and non-secure areas, with encrypted data being used for training. While it is related to the implementation and execution of AI models, it does not inherently involve prediction capabilities.

Creativity-based AI:

Title: SYSTEMS AND METHODS FOR RENDERING MODELS BASED ON MEDICAL IMAGING DATA

Patent Application Number: 20220207845
Patent Applicant/Assignee: Clarius Mobile Health Corp.

Abstract: A method of creating a 3D model, which is a visual representation of at least one physiological parameter, the method comprises deploying an AI model to execute on a computing device communicably connected to a medical imaging device, said medical imaging device acquiring medical imaging data, wherein the AI model is trained so that when it is deployed, the computing device identifies at least one physiological parameter from medical imaging data; acquiring, at the computing device, new medical imaging data; processing, using the AI model, the new medical imaging data to identify at least one physiological parameter (the at least one identified physiological parameter); employing the at least one identified physiological parameter to select a corresponding 3D model; and modifying the corresponding 3D model to alter one or more model parameters therein, to match the at least one identified physiological parameter, thereby customizing the visual appearance of the corresponding 3D model.

Explanation from LLM:

YES, the invention is related to artificial intelligence that has the ability to generate content. The AI model is trained to identify physiological parameters from medical imaging data and uses this information to select and customize a corresponding 3D model. This process involves the AI generating content (the 3D model) based on the input data (medical imaging data and identified physiological parameters).

Non-Creativity-based AI:

Title: REMOTE DOCUMENT GENERATION

Patent Application Number: 20200013034

Patent Applicant/Assignee: International Business Machines Corporation

Abstract: A method and system for generating a document is provided. The method includes generating a meta document configured to retain multiple components of different data types. A component editor directory of a component editor server is queried and a list of component editors compatible with meta document is retrieved. A first component editor of the list of component editors is selected from a remote location. The first component editor is associated with a first defined data type. A first document component comprising the first defined data type is generated within the meta document resulting in a single document comprising the first document component. A user interface is updated with the single document comprising the first document component.

Explanation from LLM:

NO, the described invention does not inherently relate to artificial intelligence that has the ability to generate content. The method and system outlined involve generating a meta document that retains multiple components of different data types, querying a directory for compatible component editors, and associating a component editor with a specific data type to generate a document component. While AI could potentially be used to enhance or automate parts of this process, the description provided does not explicitly mention the use of AI or machine learning techniques for content generation.

Engagement-based AI:

Title: VOICE ACTIVATED VIRTUAL ASSISTANT

Patent Application Number: 20130031476

Patent Applicant/Assignee: Emmett Coin, Deborah Dahl, and Richard Mandelbaum

Abstract: A method and system is presented for providing information to a user interactively using a conversation manager thereby mimicking a live personal assistant. Communication between the user and the system can be implemented orally and/or by using visual cues or other images. The conversation manager relies on a set of functions defining very flexible adaptive scripts. As a session with a user is progressing, the conversation manager, obtains information from the user refining or defining more accurately what information is required by the user. Responses from the user result in the selection of different scripts or subscripts. In the process of obtaining information, data may be collected that is available either locally, from a local sensor, or remotely from other sources. The remote sources are accessed by automatically activating an appropriate function such as a search engine and performing a search over the Internet.

Explanation from LLM:

YES, the invention is related to artificial intelligence that has the ability to interact with users. The described method and system involve a conversation manager that mimics a live personal assistant, which suggests the use of AI to process natural language, understand user intent, and provide relevant responses. The system's ability to adaptively script conversations and refine information requirements based on user input further indicates the use of AI techniques.

Non-Engagement-based AI:

Title: DELIVERING CUSTOMER INFORMATION FROM CUSTOMER CARE SITE TO CUSTOMER CARE AGENT

Patent Application Number: 20170091390

Patent Applicant/Assignee: T-Mobile US, Inc.

Abstract: A customer care site includes a plurality of pages that may individually include a call link to communicate with customer agents. When a customer tries to contact a customer agent via a call link in one of the plurality of pages on the customer care web site, a computing system associated with the customer care site transmits customer information regarding the customer's specific activities prior to selecting the call link on the customer care web site. When a customer agent responds to the customer's call, a computing device of the customer agent can display the customer information transmitted from the computing system associated with the customer care web site. As the customer agent knows about the customer's prior activities on the customer care site through access to the detailed customer information provided by the computing system, the customer agent does not need to repeat the same procedure or inquiries that the customer has already traversed on the customer care web site.

Explanation from LLM:

NO, the described invention is not directly related to artificial intelligence. It is a system designed to improve the efficiency of customer service by providing customer agents with information about a customer's previous interactions with the customer care site. This allows the agent to provide more personalized and efficient service without the need for the customer to repeat information. While the system could potentially be integrated with AI to further enhance its capabilities, the invention itself does not inherently involve AI or the ability to interact with users beyond providing information to human agents.

Appendix B. Using Retrieval-Augmented Generation (RAG) and Machine Learning to Identify Artificial Intelligence Patents

B.1 Construction of Labeled Training Data with RAG

A key component of our custom-built RAG system is a text embedding model that can map sentences or paragraphs into a dense vector space. For this purpose, we use the *sentence-transformers/all-mpnet-base-v2* model, an open-source, pre-trained embedding model that converts English text into a 768-dimensional numerical vector. This model is a well-known instance of so-called semantic embedding models, which can distinguish semantic connections between words, sentences, and documents that earlier models, such as term frequency models or word embedding models (e.g., word2vec) cannot. The *sentence-transformers/all-mpnet-base-v2* model has been trained on a diverse dataset of more than 1.17 billion text pairs, making it a general semantic embedder suitable for many use cases.³¹ We use the embedding model to convert the abstract text of every patent application in our overall sample (5,253,443 application filings) into a 768-dimensional vector.

A second key building block of our custom-built RAG system is a state-of-the-art Large Language Model (LLM) called *Phi-3-Small-8k-Instruct*. This generative AI model was developed by Microsoft Corp. and recently released to the public under an open-source license for broad commercial and research use. The model features 7 billion parameters and is an instruction-tuned version of the base *Phi-3-Small-8k* model, which was publicly released on May 21, 2024. The base *Phi-3-Small-8k* model was trained between February and April 2024 using 4.8 trillion tokens of training data from a wide variety of public sources (see <https://huggingface.co/microsoft/Phi-3-small-8k-instruct>). According to commonly-cited LLM performance benchmarks, *Phi-3-Small-8k-Instruct* is the top-performing LLM in its size class (as of mid-2024) and outperforms larger,

³¹ For more information, see <https://huggingface.co/sentence-transformers/all-mpnet-base-v2>.

proprietary models, including 2023 versions of GPT-3.5 Turbo and GPT 4 (see, for instance, the paper by Abdin et al. (2024), <https://arxiv.org/abs/2404.14219> and the LMSYS chatbot arena leaderboard³²).

With the set of embedding vectors and the generative AI model in hand, we proceed to implement Retrieval-Augmented Generation in three main steps. First, we formulate a set of five key retrieval phrases that capture the five different types of AI capabilities in our categorization scheme. The phrases include the following: “artificial intelligence that has perception ability”, “artificial intelligence that has inference ability”, “artificial intelligence that has prediction ability”, “artificial intelligence that has the ability to generate content”, and “artificial intelligence that has the ability to engage with users”. Second, the retrieval phrases are themselves converted into semantic embeddings with *sentence-transformers/all-mpnet-base-v2*, and in each year the top 1% most similar patents to each of the five phrases (in terms of highest cosine similarity between semantic embedding vectors) are retrieved. This retrieval step results in samples of patents specific to different category/year combinations. Drawing a random subsample of 100 patents from each of these category-and-year-specific samples, we obtain—for each of the five AI categories—a training sample consisting of 1,700 patents covering the time period 2007-2023. In total, there are 8,500 patents in the training samples across the five AI categories.

The third main step in implementing the RAG is to submit a sequence of queries to the LLM asking whether or not an individual training-sample patent belongs to a relevant category of AI. To reduce ambiguity and to elicit from the LLM as clear a response as possible, each prompt features a specific yes/no question in conjunction with a patent abstract as context. For example, to check whether or not U.S. Patent Application #20210209449 is related to AI with perception

³² <https://chat.lmsys.org/?leaderboard> (accessed July 2024)).

capabilities, we prompt the LLM with the following question/instruction, along with the patent abstract as context:

Is the following invention related to artificial intelligence that has perception ability?

Respond with YES or NO and give an explanation.

Graphical elements in a user interface (UI) may be detected in robotic process automation (RPA) using convolutional neural networks (CNNs). Such processes may be particularly well-suited for detecting graphical elements that are too small to be detected using ... [remaining abstract text follows]

Each training-sample patent is checked using a prompt such as the one above. Applying this querying procedure to all 8,500 training-sample patents yields training labels equal to 1 if a patent belongs to the relevant category and 0 otherwise.

To confirm the accuracy of the training labels obtained from the RAG, we also manually check some of the LLM’s predictions and explanations. Appendix A provides examples from the training data of both positive cases and negative cases, along with the explanations provided by the LLM. Based on an review of these examples and numerous others across the five AI categories, we conclude that the LLM performs well in categorizing patents and is able to distinguish fine shades of meaning in ways that simpler methods (e.g., term similarity search or semantic similarity search) cannot.

B.2 Using the Labeled Training Data to Classify all Patent Applications

Having constructed the five labeled training sets with the RAG system above, we then use them to train downstream machine-learning models that can classify all patents according to whether they belong to particular AI categories. The approach we use for this purpose is the logistic regression model, which is a type of supervised machine-learning algorithm that has been used widely for binary classification tasks in the natural and social sciences.

For each AI category, we train a logistic regression classifier using (1) the 768-dimensional semantic text-embedding vectors for the 1,700 patents comprising the relevant training set and (2) the corresponding yes/no labels provided by the RAG system. We do not use other data to train the model (e.g., characteristics of patent filers or filing year) because doing so could introduce biases into the trained model. To implement the models, we use the logistic regression class from the ‘scikit-learn’ Python package and choose the ‘liblinear’ solver for the instance. We set the parameter $C = 1.0$, which represents a moderate amount of L2 regularization. Other parameters are kept at their default values. The ‘train_test_split’ function is used to randomly split each training sample into 80% of observations for training and the rest for testing.

We assess the quality of the trained models with according to their F1 score, which is equal to the harmonic mean of a classifier’s ‘precision’ and ‘recall’ scores. (Precision is the number of true positives divided by the sum of true positives and negatives; recall is the number of true positives divided by the sum of true and false positives.) Since the fitted probabilities from a logistic regression are continuous, it is necessary to specify threshold cutoff values to map probabilities to binary outcomes. For each model, we calculate numerically the thresholds that maximize the F1 score. For the Perception, Inference, Prediction, Creativity, and Engagement models, the F1 scores under the optimal thresholds are, respectively, 72%, 82%, 87%, 74%, and 81%.

Finally, we use the trained classifiers to make out-of-sample predictions about whether each instance in the entire sample (approximately 5 million patent application filings) belongs to a given AI category. Note that, when mapping predicted probabilities into binary outcomes, we do not simply use the F1-optimal thresholds identified in the training step because the training datasets consist of patents that are more similar than the average patent to a particular text query (in semantic embedding space). Instead, for each AI category we define a patent as being of that type if and only if its predicted probability is 0.75 or greater.

Appendix C. Additional Tables

Table C1. Characteristics of AI Patents by Category

This table reports summary statistics for patent-level observations for the sample period 2007-2023. Patent data are from the USPTO Bulk Data Storage System (BDSS). The sample consists of patent grants in the USPTO bulk data that are filed by companies in CRSP/Compustat. AI patents are identified and categorized using a Retrieval-Augmented Generation (RAG) model and a downstream machine-learning classifier as described in Section 3.2 and Appendix B. The AI categories include perception-based AI, inference-based AI, prediction-based AI, creativity-based AI, and engagement-based AI. Patent categories are not mutually exclusive. A patent is categorized to be within a category if its predicted probability score (from the downstream machine-learning classifier) exceeds 0.75. *Citations, 3yr* is the total number of forward citations that a patent grant receives in the three years following the year of filing. *Breadth* is the number of distinct IPC (International Patent Classification) codes associated with a patent. *Originality* is one minus the Herfindahl Index of the three-digit technology class distribution of all the patents it cites. *Generality* is one minus the Herfindahl Index of the three-digit technology class distribution of all the patents that cite it. Following Kogan et al. (2017), *Patent value (appl)* is the dollar value of a patent measured over the event window [-1, +1] around the public disclosure date of the application. *Patent value (grant)* is the dollar value of a patent measured over the event window [-1, +1] around the public disclosure date of the grant. The details of variable construction are provided in Section 3.4.

| <i>Perception AI</i> | N | Mean | Std. Dev. | p10 | Median | p90 |
|-----------------------------|-------|------------|------------|--------|-----------|------------|
| Breadth | 2,258 | 1.658 | 0.918 | 1 | 1 | 3 |
| Originality | 2,258 | 0.122 | 0.238 | 0 | 0 | 0.5 |
| Generality | 2,258 | 0.064 | 0.183 | 0 | 0 | 0.463 |
| Citations, 3yr | 2,258 | 0.045 | 0.207 | 0 | 0 | 0 |
| Patent value (appl) | 2,138 | 68,264.51 | 102,823.49 | 303.84 | 18,262.63 | 269,778.25 |
| Patent value (grant) | 2,071 | 102,482.01 | 148,496.39 | 464.77 | 26,547.71 | 384,056.13 |

| <i>Inference AI</i> | N | Mean | Std. Dev. | p10 | Median | p90 |
|----------------------------|-------|------------|------------|--------|-----------|------------|
| Breadth | 4,809 | 1.486 | 0.765 | 1 | 1 | 2 |
| Originality | 4,809 | 0.116 | 0.226 | 0 | 0 | 0.5 |
| Generality | 4,809 | 0.055 | 0.165 | 0 | 0 | 0.231 |
| Citations, 3yr | 4,809 | 0.048 | 0.215 | 0 | 0 | 0 |
| Patent value (appl) | 4,485 | 70,917.64 | 102,202.44 | 437.68 | 21,686.85 | 263,453.47 |
| Patent value (grant) | 4,333 | 112,388.30 | 153,372.78 | 909.51 | 35,177.14 | 434,081.41 |

| <i>Prediction AI</i> | N | Mean | Std. Dev. | p10 | Median | p90 |
|-----------------------------|--------|-----------|------------|--------|-----------|------------|
| Breadth | 10,772 | 1.54 | 0.816 | 1 | 1 | 3 |
| Originality | 10,772 | 0.114 | 0.227 | 0 | 0 | 0.5 |
| Generality | 10,772 | 0.048 | 0.158 | 0 | 0 | 0 |
| Citations, 3yr | 10,772 | 0.036 | 0.185 | 0 | 0 | 0 |
| Patent value (appl) | 9,873 | 58,840.63 | 92,633.68 | 354.43 | 15,802.27 | 194,817.34 |
| Patent value (grant) | 9,634 | 88,271.22 | 135,712.04 | 628.32 | 22,869.79 | 314,729.88 |

Continued on next page

Table C1, continued

| <i>Creativity AI</i> | N | Mean | Std. Dev. | p10 | Median | p90 |
|-----------------------------|-------|------------|------------|--------|-----------|------------|
| Breadth | 2,782 | 1.422 | 0.704 | 1 | 1 | 2 |
| Originality | 2,782 | 0.099 | 0.21 | 0 | 0 | 0.5 |
| Generality | 2,782 | 0.047 | 0.154 | 0 | 0 | 0 |
| Citations, 3yr | 2,782 | 0.052 | 0.222 | 0 | 0 | 0 |
| Patent value (appl) | 2,615 | 74,854.08 | 104,268.56 | 466.26 | 26,154.44 | 279,007.44 |
| Patent value (grant) | 2,528 | 121,566.05 | 158,930.08 | 968.66 | 39,529.45 | 470,911.50 |

| <i>Engagement AI</i> | N | Mean | Std. Dev. | p10 | Median | p90 |
|-----------------------------|--------|-----------|------------|--------|-----------|------------|
| Breadth | 11,384 | 1.559 | 0.781 | 1 | 1 | 3 |
| Originality | 11,384 | 0.113 | 0.225 | 0 | 0 | 0.5 |
| Generality | 11,384 | 0.048 | 0.157 | 0 | 0 | 0 |
| Citations, 3yr | 11,384 | 0.042 | 0.2 | 0 | 0 | 0 |
| Patent value (appl) | 10,561 | 61,463.48 | 96,283.62 | 322.93 | 16,281.38 | 213,439.52 |
| Patent value (grant) | 10,405 | 94,240.05 | 141,124.17 | 507.56 | 24,818.91 | 345,704.78 |

| <i>Non-AI patents</i> | N | Mean | Std. Dev. | p10 | Median | p90 |
|------------------------------|-----------|-----------|-----------|--------|-----------|------------|
| Breadth | 1,236,217 | 1.488 | 0.776 | 1 | 1 | 3 |
| Originality | 1,236,217 | 0.07 | 0.189 | 0 | 0 | 0.5 |
| Generality | 1,236,217 | 0.023 | 0.111 | 0 | 0 | 0 |
| Citations, 3yr | 1,236,217 | 0.021 | 0.143 | 0 | 0 | 0 |
| Patent value (appl) | 1,095,828 | 29,952.86 | 60,532.74 | 188.03 | 8,165.76 | 79,659.45 |
| Patent value (grant) | 1,133,546 | 40,915.09 | 83,500.94 | 184.24 | 10,876.52 | 109,545.03 |

Table C2. AI Innovation and Firm Employment - 2SLS First stage Regression

This table reports the first-stage results of 2SLS regression examining the effects of AI innovation on firm employment growth. The dependent variables in Columns (1), (3), (5), (7), and (9) are the log-transformed number of patent grants in an AI category filed for by the firm during the year. The dependent variables in Columns (2), (4), (6), (8), and (10) are the log-transformed number of all other patent grants filed for in the year by the firm. The instruments in each regression are (1) the average adjusted patent examiner leniency for the firm's AI patent applications filed within a given AI category during the year and (2) the average adjusted patent examiner leniency for the firm's other patent applications filed during the year. Control variables are defined in Table 3. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for each category of patent application in the regression, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---------------------------------------|---|------------------------------|---|------------------------------|--|------------------------------|---|------------------------------|--|------------------------------|
| IV-2SLS (1st Stage) | | | | | | | | | | |
| AI Type k = | | | | | | | | | | |
| | <i>Perception</i> | | <i>Inference</i> | | <i>Prediction</i> | | <i>Creativity</i> | | <i>Engagement</i> | |
| VARIABLES | Log # of AI patents of type <i>k</i> | Log # of other patents | Log # of AI patents of type <i>k</i> | Log # of other patents | Log # of AI patents of type <i>k</i> | Log # of other patents | Log # of AI patents of type <i>k</i> | Log # of other patents | Log # of AI patents of type <i>k</i> | Log # of other patents |
| IV_AI patents of type <i>k</i> | 0.638*** (0.106) | 0.345** (0.151) | 0.888*** (0.083) | 0.033 (0.111) | 0.946*** (0.059) | 0.042 (0.080) | 0.276** (0.109) | 0.285** (0.130) | 1.178*** (0.080) | 0.551*** (0.103) |
| IV_other patents | 0.001 (0.003) | 1.008*** (0.033) | 0.003 (0.004) | 1.004*** (0.033) | 0.009 (0.006) | 1.003*** (0.033) | 0.001 (0.003) | 0.998*** (0.033) | 0.007 (0.005) | 0.998*** (0.033) |
| Log sale | -0.001 (0.001) | -0.098*** (0.011) | -0.003** (0.001) | -0.098*** (0.011) | -0.007*** (0.002) | -0.095*** (0.010) | -0.002*** (0.001) | -0.097*** (0.011) | -0.004** (0.002) | -0.095*** (0.010) |
| MTB | -0.001 (0.000) | -0.004 (0.003) | -0.000 (0.001) | -0.004 (0.003) | -0.000 (0.001) | -0.004 (0.003) | -0.000 (0.000) | -0.004 (0.003) | -0.000 (0.001) | -0.004 (0.003) |
| ROA | 0.001 (0.003) | 0.071*** (0.025) | 0.008** (0.004) | 0.066*** (0.024) | 0.006 (0.005) | 0.061** (0.024) | 0.004* (0.002) | 0.065*** (0.025) | 0.007 (0.004) | 0.062** (0.024) |
| R&D | 0.001 (0.001) | -0.097*** (0.013) | -0.002 (0.002) | -0.093*** (0.013) | -0.002 (0.002) | -0.094*** (0.012) | -0.001 (0.001) | -0.094*** (0.013) | -0.002 (0.002) | -0.089*** (0.012) |
| R&D missing | -0.008 (0.006) | -0.259*** (0.061) | -0.016** (0.006) | -0.253*** (0.060) | -0.016 (0.011) | -0.250*** (0.058) | -0.009* (0.005) | -0.251*** (0.059) | -0.006 (0.009) | -0.233*** (0.058) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # of AI type <i>k</i> apps × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # of other apps × year FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sanderson-Windmeijer F | 62.47 | 916.30 | 124.85 | 918.86 | 291.52 | 929.69 | 11.88 | 901.79 | 513.22 | 926.74 |
| Sanderson-Windmeijer Chi-sq | 65.07 | 954.31 | 129.97 | 956.55 | 304.19 | 970.11 | 12.38 | 939.07 | 535.19 | 966.42 |
| Observations | 13,741 | 13,741 | 13,741 | 13,741 | 13,741 | 13,741 | 13,741 | 13,741 | 13,741 | 13,741 |
| R-squared | 0.025 | 0.009 | 0.017 | 0.025 | 0.009 | 0.017 | 0.025 | 0.009 | 0.017 | 0.017 |

Table C3. AI Innovation and Firm Value - 2SLS First stage Regression

This table reports the first-stage results of 2SLS regression examining the effects of AI innovation on firm value. The dependent variables include Log # of augmenting AI patents, Log # of non-augmenting AI patents, Log # of displacing AI patents, Log # of non-displacing AI patents, Log # of non-augmenting-displacing AI patents. *Log # of augmenting (displacing) AI patents* the log-transformed number of patent grants in AI categories that have positive (negative) association with firms' skilled labor growth during the year, and all other patents are counted as *Log # of non-augmenting (non-displacing) AI patents*. The instruments in each regression include (1) the average adjusted patent examiner leniency for the firm's augmenting AI patents during the year (2) the average adjusted patent examiner leniency for the firm's augmenting AI patents during the year and (3) the average adjusted patent examiner leniency for the firm's other patent applications filed during the year. Control variables are defined in Table 3. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for each category of patent application in the regression, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

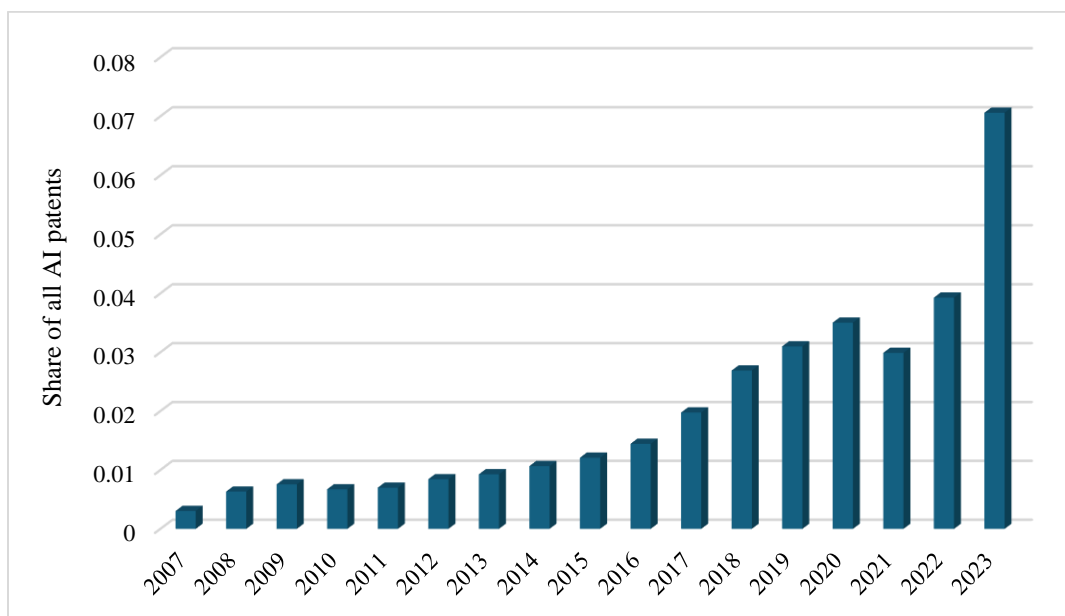
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------------------------|--------------------------------------|--|--------------------------------------|--|--------------------------------------|--------------------------------------|--|
| VARIABLES | IV-2SLS (1st Stage) | | | | | | |
| | Log # of augmenting AI patents | Log # of non- augmenting AI patents | Log # of displacing AI patents | Log # of non- displacing AI patents | Log # of augmenting AI patents | Log # of displacing AI patents | Log # of non- augmenting- displacing AI patents |
| IV_augmenting_AI | 0.726*** (0.074) | 0.078 (0.048) | | | 0.639*** (0.074) | 0.030 (0.059) | -0.009 (0.059) |
| IV_non-augmenting_AI | -0.001 (0.004) | 0.807*** (0.032) | | | | | |
| IV_displacing_AI | | | 1.108*** (0.095) | 0.308*** (0.076) | 0.247*** (0.086) | 1.025*** (0.098) | 0.210** (0.087) |
| IV_non-displacing_AI | | | -0.006 (0.004) | 0.805*** (0.032) | | | |
| IV_non_augmenting_displacing_AI | | | | | -0.002 (0.004) | -0.003 (0.004) | 0.808*** (0.032) |
| Log sale | -0.041*** (0.007) | -0.087*** (0.007) | -0.085*** (0.007) | -0.087*** (0.007) | -0.001 (0.002) | -0.042*** (0.007) | 0.000 (0.001) |
| MTB | -0.000 (0.002) | -0.087*** (0.007) | -0.085*** (0.007) | -0.087*** (0.007) | -0.000 (0.001) | 0.000 (0.002) | 0.001 (0.000) |
| ROA | 0.058*** (0.022) | 0.015*** (0.003) | 0.015*** (0.003) | 0.015*** (0.003) | 0.007* (0.004) | 0.060*** (0.021) | 0.005 (0.004) |
| R&D | -0.018** | 0.000 | 0.001 | 0.001 | 0.004** | -0.018** | -0.001 |

| | | | | | | | |
|--|------------------------------|------------------------------|------------------------------|------------------------------|-----------------------------|------------------------------|------------------------------|
| R&D missing | (0.008) -0.030 (0.040) | (0.001) -0.006 (0.006) | (0.001) -0.007 (0.006) | (0.001) -0.006 (0.006) | (0.002) 0.002 (0.007) | (0.008) -0.033 (0.041) | (0.001) -0.003 (0.005) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # of augmenting AI apps × year FEs | Yes | Yes | | | | | |
| # of non-augmenting AI apps × year FEs | Yes | Yes | | | | | |
| # of displacing AI apps × year FEs | | | Yes | Yes | Yes | Yes | Yes |
| # of non-displacing AI apps × year FEs | | | Yes | Yes | | | |
| # of all other apps × year FEs | | | | | Yes | Yes | Yes |
| Sanderson-Windmeijer F | 119.83 | 639.06 | 282.21 | 644.09 | 90.37 | 135.63 | 643.49 |
| Sanderson-Windmeijer Chi-sq | 125.67 | 670.19 | 295.66 | 674.80 | 94.77 | 142.24 | 674.85 |
| Observations | 13,771 | 13,741 | 13,741 | 13,741 | 13,770 | 13,770 | 13,771 |

Figure 1. Time-Series Distribution of Artificial Intelligence (AI) Patents

This figure illustrates the time-series distribution of AI patents from 2007 to 2023. Patent data are from the USPTO Bulk Data Storage System (BDSS). The sample consists of patent applications that are filed by U.S. public companies belonging to CRSP/Compustat. Details of the matching between USPTO and CRSP/Compustat data are provided in the text. Panel A reports the distribution of AI patents over time as a fraction of all patents, and Panel B reports the distributions over time of different types of AI patents as fractions of all AI patents. AI patents are identified and categorized using a Retrieval-Augmented Generation (RAG) model and a downstream machine-learning classifier as described in Section 3.2 and Appendix B. The AI categories include perception-based AI, inference-based AI, prediction-based AI, creativity-based AI, and engagement-based AI.

Panel A: AI Patents as a Fraction of All Patents



Panel B: Time-Series Distributions of Different Types of AI Patents (as Fractions of All AI Patents)

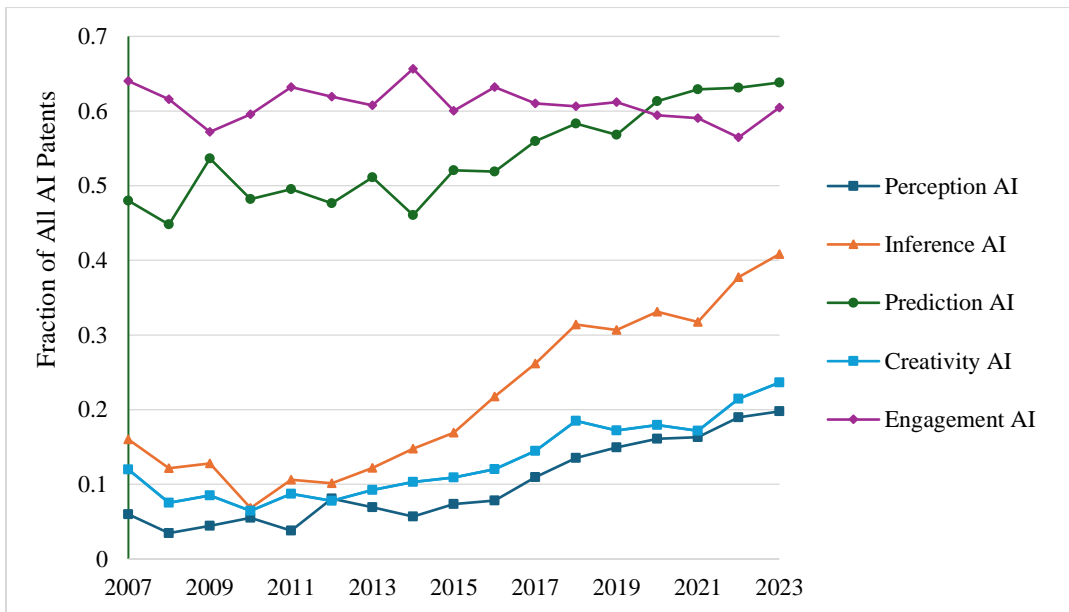
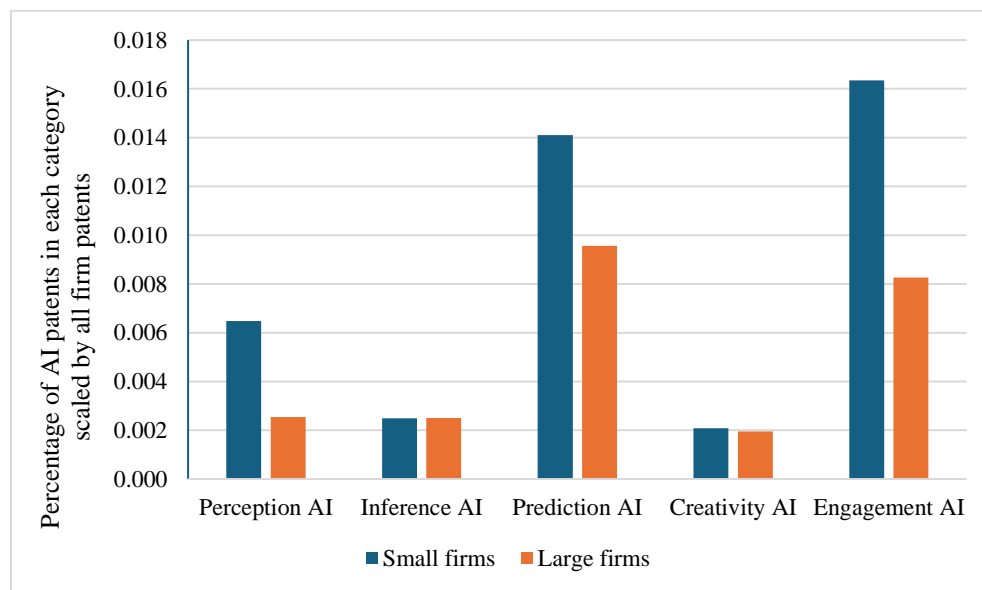


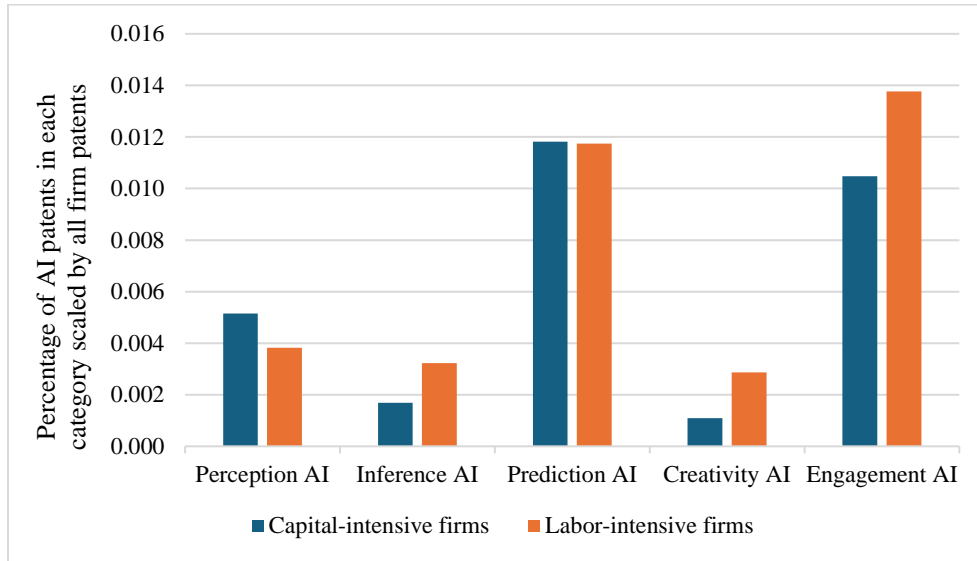
Figure 2. AI Innovation Activity by Firm Characteristics

This figure shows AI innovation activity by firms over 2007-2023 according to key firm characteristics. Patent data are from the USPTO Bulk Data Storage System (BDSS). Panel A shows, for small and large firms in the CRSP/Compustat database, the annual amount of AI patenting (by category) as a fraction of all patents filed by the relevant group of firms. Large (small) firms are those with total assets above (below) the sample median for the year. Panel B reports annual AI patenting (by category) as fractions of all patents filed by labor-intensive firms and all patents filed by capital-intensive firms. A firm is labor-intensive (capital-intensive) in a year if its labor share, i.e., its total employment scaled by total assets, is above (below) the sample median for the year. Panel C reports annual AI patenting (by category) as fractions of all patents filed by R&D-intensive firms and all patents non-R&D-intensive firms. A firm is defined as R&D-intensive in a year if and only if its R&D intensity (R&D expenditures scaled by total assets) is above the sample median during the year. Firm employment data are obtained from the Revelio Labs database. Other firm-level data are from Compustat. AI patents are identified and categorized using a Retrieval-Augmented Generation (RAG) model and a downstream machine-learning classifier as described in Section 3.2 and Appendix B. The AI categories include perception-based AI, inference-based AI, prediction-based AI, creativity-based AI, and engagement-based AI.

Panel A. AI Innovation Activity in Small vs. Large Firms



Panel B. AI Innovations in Labor intensive vs. Capital intensive Firms



Panel C. AI Innovations in R&D intensive vs. Non-R&D intensive Firms

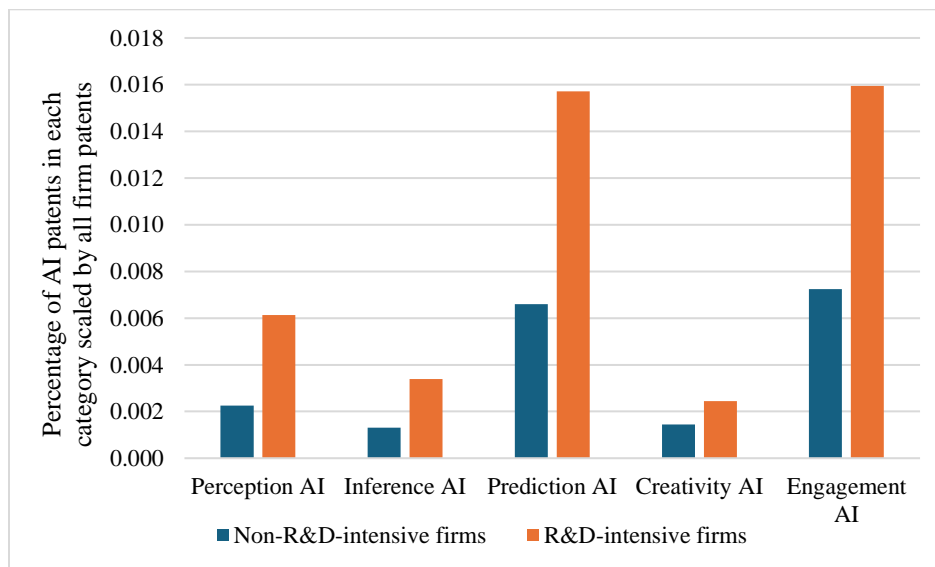


Table 1. Categories of AI, Tasks/Capabilities, and Examples

This table shows a proposed categorization of AI technology based on five functional capabilities that correspond to key aspects of human intelligence. The descriptions of examples, tasks and capabilities are based on the authors' reading of public news articles and research papers, and industry reports.

| Functional Category | Tasks and Capabilities | Examples of AI applications |
|----------------------------|--|--|
| <i>Perception</i> | Image and speech recognition; object detection; Sensory fusion; Tactile (touch) perception | Computer vision systems; Autonomous vehicle systems; Diagnostic medical imaging; Augmented reality (AR) and Virtual reality (VR) |
| <i>Inference</i> | Logical reasoning; Heuristic inference; Decision making; Optimization in deep learning | Expert systems; AlphaGo; automated reasoning systems; C++ coding assistants; Robo-advisors |
| <i>Prediction</i> | Data-centric forecasting; Machine learning; Natural language processing; Risk assessment | AlphaFold protein structure prediction; Fraud detection systems; Credit scoring; Product recommendation; AI-powered push advertising |
| <i>Creativity</i> | Text, image, sound, video, and art generation; Procedural content generation; Content transformation | ChatGPT; Adobe Firefly art generator; OpenAI Sora video generator; Robotic painters and sculptors |
| <i>Engagement</i> | Interactive chat; interactive content generation; Customization; Emotion detection; Contextual awareness | Siri; Cortana; Alexa; Chat GPT; customer service AI; Videogame NPCs; Smart home devices; Self-driving delivery robot |

Table 2. Summary Statistics: Artificial Intelligence Innovation Activity

This table reports statistics on the incidence of AI patents within industrial sectors (Panel A and B) and within the top five most heavily represented IPC classes (Panel C and D) during 2007-2023. Patent data are from the USPTO Bulk Data Storage System (BDSS). The sample consists of patent applications and grants in the USPTO bulk data storage system (BDSS) that are filed by companies belonging to CRSP/Compustat. AI patents are identified and categorized using a Retrieval-Augmented Generation (RAG) model and a downstream machine-learning classifier as described in Section 3.2 and Appendix B. The AI categories include perception-based AI, inference-based AI, prediction-based AI, creativity-based AI, and engagement-based AI.

Panel A. Industry distribution of AI patent applications

| SIC (one-digit) | Description | All AI | Perception | Inference | Prediction | Creativity | Engagement |
|-----------------|---|--------|------------|-----------|------------|------------|------------|
| 7 | Transport; storage and communication | 19,195 | 1,138 | 2,943 | 5,707 | 2,098 | 7,309 |
| 3 | Manufacturing | 16,448 | 1,412 | 2,584 | 5,844 | 1,263 | 5,345 |
| 4 | Electricity; gas and water supply | 3,309 | 298 | 479 | 1,039 | 235 | 1,258 |
| 6 | Wholesale and retail trade | 2,114 | 125 | 380 | 784 | 199 | 626 |
| 2 | Mining and quarrying | 1,238 | 95 | 248 | 587 | 68 | 240 |
| 9 | Community; social and personal services | 1,080 | 79 | 182 | 565 | 53 | 201 |
| 5 | Construction | 1,004 | 56 | 154 | 296 | 110 | 388 |
| 8 | Financial; insurance; real estate and business services | 819 | 44 | 132 | 336 | 72 | 235 |
| 1 | Agriculture; hunting; forestry and fishing | 354 | 23 | 72 | 181 | 22 | 56 |
| 0 | Others | 2 | 0 | 0 | 1 | 0 | 1 |

Panel B. Industry distribution of AI patent grants

| SIC (one-digit) | Description | All AI | Perception | Inference | Prediction | Creativity | Engagement |
|-----------------|---|--------|------------|-----------|------------|------------|------------|
| 7 | Transport; storage and communication | 17,335 | 970 | 2,590 | 5,221 | 1,839 | 6,715 |
| 3 | Manufacturing | 14,502 | 1,183 | 2,188 | 5,289 | 1,044 | 4,798 |
| 4 | Electricity; gas and water supply | 2,627 | 226 | 352 | 838 | 170 | 1,041 |
| 6 | Wholesale and retail trade | 1,573 | 91 | 271 | 616 | 141 | 454 |
| 2 | Mining and quarrying | 886 | 63 | 169 | 458 | 45 | 151 |
| 9 | Community; social and personal services | 810 | 55 | 126 | 465 | 35 | 129 |
| 5 | Construction | 730 | 35 | 107 | 220 | 75 | 293 |
| 8 | Financial; insurance; real estate and business services | 681 | 38 | 101 | 288 | 60 | 194 |
| 1 | Agriculture; hunting; forestry and fishing | 241 | 13 | 46 | 133 | 12 | 37 |
| 0 | Others | 2 | 0 | 0 | 1 | 0 | 1 |

Panel C. Distribution of AI patent applications among key IPC classes

| IPC (three-digit) | Description | All AI | Perception | Inference | Prediction | Creativity | Engagement |
|-------------------|-------------------------------------|--------|------------|-----------|------------|------------|------------|
| G06 | Computing, Calculating, or Counting | 36,979 | 2,750 | 6,175 | 12,893 | 3,578 | 11,583 |
| H04 | Electric Communication Technique | 9,178 | 514 | 1,447 | 3,065 | 594 | 3,558 |
| G10 | Musical Instruments; Acoustics | 7,363 | 423 | 888 | 765 | 864 | 4,423 |
| G05 | Controlling; Regulating | 2,157 | 345 | 282 | 1,078 | 87 | 365 |
| G01 | Measuring; Testing | 1,567 | 165 | 194 | 976 | 32 | 200 |

Panel C. Distribution of AI patent grants among key IPC classes

| IPC (three-digit) | Description | All AI | Perception | Inference | Prediction | Creativity | Engagement |
|-------------------|-------------------------------------|--------|------------|-----------|------------|------------|------------|
| G06 | Computing, Calculating, or Counting | 25,686 | 1,938 | 4,094 | 8,585 | 2,376 | 8,693 |
| H04 | Electric Communication Technique | 7,651 | 442 | 1,116 | 2,458 | 467 | 3,168 |
| G10 | Musical Instruments; Acoustics | 6,172 | 332 | 745 | 660 | 754 | 3,681 |
| G05 | Controlling; Regulating | 1,760 | 275 | 205 | 919 | 63 | 298 |
| G01 | Measuring; Testing | 1,438 | 146 | 170 | 842 | 32 | 248 |

Table 3. Characteristics of Firm AI Innovation and Employment

This table reports summary statistics for firm-year innovation and employment outcomes during the sample period 2007-2023. All firm-level variables are measured as of the fiscal-year end preceding the initial publication date of the patent filing. Patents in each AI category are identified from the RAG model and the downstream machine-learning classifier as described in Section 3.2 and Appendix B. Firm employment data are obtained from the Revelio Labs database. Panel A reports, at the firm-year level, the frequencies of AI patents within each category and for categories defined on the basis of estimated firm-level employment effects. Patents are defined as *Skilled-Labor augmenting (displacing) AI* if, according to Table 4, the given category of AI innovation has a positive (negative) estimated effect on the firm's subsequent skilled-labor growth. Panel B reports, at the firm-year level, employment outcomes and financial characteristics. *Skilled-labor growth* is a firm's net growth in skilled labor over the following year. Skilled labor is defined as the number of employees in the firm who hold roles in which more than 25 percent of workers have earned at least a bachelor's degree. *Skilled-labor reskilling* is a firm's net growth in internal inflow for skilled labor over the following year. *Skilled-labor external hiring* is a firm's net growth in external inflow for skilled labor over the following year. *Skilled-labor job separation* is the net change in a firm's skilled employee departures over the following year. *Skilled-labor core (scope) augmentation* is the net growth of skilled labor in old (new) job roles over the following year. A job role is defined as new if it did not show up in the firm's employment history prior to the past three years. *Unskilled-labor growth* is a firm's net growth in unskilled labor during the year. *Tobin's Q* is the average ratio of the book value of debt (Compustat items *DLTT* + *DLC*) plus the market value of equity (Compustat items $PRCC_F \times CSHO$) minus the firm's current assets (Compustat item *ACT*) to the book value of property, plant, and equipment (Compustat item *PPEGT*) over following two years. *Log sales* is the natural log of total sales in the prior year from Compustat. *MTB* is the market to book ratio in the prior year. *ROA* is income before extraordinary items divided by total assets in the prior year. *R&D* is the natural log of R&D expenditures in the prior year. Missing values of R&D are imputed as zero and indicated by *R&D Missing*.

Panel A. Annual Firm-Level AI Innovation, by Functional Category

| | N | Mean | Std. Dev. | p10 | Median | p90 |
|-----------------------------|--------|-------|-----------|-----|--------|-----|
| <i>Patent applications</i> | | | | | | |
| Perception AI | 18,937 | 0.181 | 0.892 | 0 | 0 | 0 |
| Inference AI | 18,937 | 0.426 | 1.899 | 0 | 0 | 1 |
| Prediction AI | 18,937 | 1.130 | 4.495 | 0 | 0 | 2 |
| Creativity AI | 18,937 | 0.191 | 0.982 | 0 | 0 | 0 |
| Engagement AI | 18,937 | 0.768 | 3.581 | 0 | 0 | 1 |
| Skilled-labor augmenting AI | 18,937 | 0.887 | 4.158 | 0 | 0 | 1 |
| Skilled-labor displacing AI | 18,937 | 0.426 | 1.899 | 0 | 0 | 1 |
| <i>Patent grants</i> | | | | | | |
| Perception AI | 18,937 | 0.117 | 0.619 | 0 | 0 | 0 |
| Inference AI | 18,937 | 0.266 | 1.261 | 0 | 0 | 0 |
| Prediction AI | 18,937 | 0.694 | 2.876 | 0 | 0 | 1 |
| Creativity AI | 18,937 | 0.116 | 0.630 | 0 | 0 | 0 |
| Engagement AI | 18,937 | 0.498 | 2.372 | 0 | 0 | 1 |
| Skilled-labor augmenting AI | 18,937 | 0.560 | 2.637 | 0 | 0 | 1 |
| Skilled-labor displacing AI | 18,937 | 0.266 | 1.261 | 0 | 0 | 0 |

Continued on next page

Table 3, continued

Panel B. Annual Firm-Level Employment Outcomes and Financial Characteristics

| <i>Employment and Financial Characteristics</i> | N | Mean | Std. Dev. | p10 | Median | p90 |
|---|--------|--------|-----------|--------|--------|--------|
| Skilled-labor growth | 18,937 | 0.083 | 0.313 | -0.246 | 0.024 | 0.435 |
| Skilled-labor reskilling | 18,937 | 0.057 | 0.051 | 0.000 | 0.054 | 0.127 |
| Skilled-labor external hiring | 18,937 | 0.201 | 0.191 | 0.000 | 0.179 | 0.407 |
| Skilled-labor job separation | 18,937 | -0.180 | 0.198 | -0.421 | -0.178 | 0.000 |
| Skilled-labor core augmentation | 18,937 | 0.043 | 0.275 | -0.223 | 0.000 | 0.329 |
| Skilled-labor scope augmentation | 18,937 | 0.039 | 0.211 | -0.066 | 0.000 | 0.226 |
| Unskilled-labor growth | 18,937 | -0.070 | 0.212 | -0.319 | -0.042 | 0.122 |
| Tobin's Q | 15,372 | 14.536 | 36.122 | 0.387 | 3.805 | 32.042 |
| Log sale | 18,935 | 6.446 | 2.902 | 2.384 | 6.710 | 10.070 |
| MTB | 18,200 | 2.520 | 2.037 | 1.011 | 1.834 | 4.825 |
| ROA | 18,912 | -0.011 | 0.333 | -0.391 | 0.096 | 0.211 |
| R&D | 18,937 | 3.516 | 2.251 | 0.000 | 3.553 | 6.524 |
| R&D missing | 18,937 | 0.131 | 0.338 | 0.000 | 0.000 | 1.000 |

Table 4. Effects of AI Innovation on Growth in Skilled Labor

This table reports the second-stage results of 2SLS regressions examining the effects of AI innovation on firms' growth in skilled labor. The first-stage results are reported in Appendix C, Table C2. The endogenous variables in each regression are (1) the log-transformed number of patent grants within an AI category that were filed for by the firm during the year and (2) the log-transformed number of all other patent grants that were filed for by the firm during the year. The instruments in each regression are (1) the average adjusted patent examiner leniency for the firm's within-category AI patent applications during the year and (2) the average adjusted patent examiner leniency for the firm's other patent applications during the year. The dependent variable, *Skilled-labor growth* is a firm's net growth in skilled labor over the following year. Skilled labor is defined as the number of employees who hold roles for which more than 25 percent of workers have earned at least a bachelor's degree. Control variables are defined as in Table 3. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for both within-category patents and for all other patents, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| | Skilled Labor Growth | | | | |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| | AI Type $k =$ | | | | |
| | <i>Perception</i> | <i>Inference</i> | <i>Prediction</i> | <i>Creativity</i> | <i>Engagement</i> |
| Log # of AI patents of type k | 0.388** (0.155) | -0.152** (0.071) | -0.063 (0.055) | 0.472 (0.316) | 0.139** (0.054) |
| Log # of other patents | -0.044* (0.026) | -0.042 (0.026) | -0.045* (0.026) | -0.047* (0.026) | -0.047* (0.026) |
| Log sale | -0.080*** (0.009) | -0.080*** (0.008) | -0.080*** (0.008) | -0.079*** (0.008) | -0.079*** (0.008) |
| MTB | -0.003 (0.003) | -0.003 (0.003) | -0.003 (0.003) | -0.002 (0.003) | -0.003 (0.003) |
| ROA | 0.142*** (0.024) | 0.142*** (0.024) | 0.139*** (0.024) | 0.140*** (0.024) | 0.139*** (0.024) |
| R&D | -0.119*** (0.010) | -0.116*** (0.010) | -0.116*** (0.010) | -0.117*** (0.010) | -0.116*** (0.010) |
| R&D missing | -0.312*** (0.052) | -0.310*** (0.051) | -0.306*** (0.051) | -0.302*** (0.052) | -0.309*** (0.051) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| # of AI type k apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| # of other apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 30.45 | 183.28 | 449.37 | 6.43 | 483.57 |
| Observations | 17,391 | 17,376 | 17,414 | 17,395 | 17,380 |
| R-squared | 0.071 | 0.060 | 0.062 | 0.066 | 0.072 |

Table 5. Effects of AI Innovation on Skilled Labor Growth: Reskilling, External Hiring, and Job Separation

This table reports the second-stage results of 2SLS regression examining the effects of AI innovation on firms' skilled-labor growth through reskilling (Panel A), external hiring (Panel B), and job separation (Panel C). The endogenous variables and instruments in each regression are as in Table 4. *Skilled-labor reskilling* is a firm's net growth in internal inflow for skilled labor in the following year. *Skilled-labor external hiring* is a firm's net growth in external inflow for skilled labor in the following year. *Skilled-labor job separation* is a firm's net changes in employee departure for skilled labor in the following year. Control variables are defined as in Table 3. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for both within-category patents and for all other patents, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| Panel A. Skilled-labor Reskilling | | | | | |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| AI Type $k =$ | | | | | |
| | <i>Perception</i> | <i>Inference</i> | <i>Prediction</i> | <i>Creativity</i> | <i>Engagement</i> |
| Log # of AI patents of type k | 0.037* (0.020) | -0.030*** (0.012) | -0.013* (0.007) | 0.023 (0.037) | 0.010 (0.007) |
| Log # of other patents | 0.003 (0.004) | 0.003 (0.004) | 0.004 (0.004) | 0.003 (0.004) | 0.003 (0.004) |
| Log sale | -0.002** (0.001) | -0.002** (0.001) | -0.002** (0.001) | -0.002** (0.001) | -0.002** (0.001) |
| MTB | -0.001*** (0.000) | -0.001*** (0.000) | -0.001*** (0.000) | -0.001*** (0.000) | -0.001*** (0.000) |
| ROA | 0.010*** (0.003) | 0.010*** (0.003) | 0.010*** (0.003) | 0.010*** (0.003) | 0.010*** (0.003) |
| R&D | -0.002* (0.001) | -0.002 (0.001) | -0.002 (0.001) | -0.002 (0.001) | -0.002 (0.001) |
| R&D missing | -0.013* (0.006) | -0.013** (0.006) | -0.013** (0.006) | -0.012* (0.006) | -0.012* (0.006) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| # of AI type k apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| # of other apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 30.45 | 183.28 | 449.37 | 6.43 | 483.57 |
| Observations | 17,391 | 17,376 | 17,414 | 17,395 | 17,380 |
| R-squared | 0.021 | 0.005 | 0.013 | 0.021 | 0.022 |

Table 5, continued

| Panel B. Skilled-labor External Hiring | | | | | |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| AI Type $k =$ | | | | | |
| | <i>Perception</i> | <i>Inference</i> | <i>Prediction</i> | <i>Creativity</i> | <i>Engagement</i> |
| Log # of AI patents of type k | 0.171** (0.072) | -0.065* (0.036) | -0.047* (0.025) | 0.263* (0.143) | 0.081*** (0.025) |
| Log # of other patents | -0.009 (0.015) | -0.008 (0.015) | -0.008 (0.015) | -0.011 (0.016) | -0.011 (0.016) |
| Log sale | -0.031*** (0.005) | -0.032*** (0.005) | -0.032*** (0.005) | -0.031*** (0.005) | -0.031*** (0.005) |
| MTB | 0.002 (0.001) | 0.002 (0.002) | 0.001 (0.002) | 0.002 (0.001) | 0.002 (0.002) |
| ROA | 0.030** (0.015) | 0.032** (0.015) | 0.030* (0.015) | 0.031** (0.015) | 0.030* (0.015) |
| R&D | -0.047*** (0.005) | -0.046*** (0.005) | -0.046*** (0.005) | -0.046*** (0.005) | -0.046*** (0.005) |
| R&D missing | -0.148*** (0.027) | -0.148*** (0.027) | -0.147*** (0.027) | -0.143*** (0.027) | -0.147*** (0.027) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| # of AI type k apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| # of other apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 30.45 | 183.28 | 449.37 | 6.43 | 483.57 |
| Observations | 17,391 | 17,376 | 17,414 | 17,395 | 17,380 |
| R-squared | 0.042 | 0.038 | 0.037 | 0.034 | 0.044 |

Table 5, continued

| Panel C. Skilled-labor Job Separation | | | | | |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| AI Type $k =$ | | | | | |
| | <i>Perception</i> | <i>Inference</i> | <i>Prediction</i> | <i>Creativity</i> | <i>Engagement</i> |
| Log # of AI patents of type k | 0.180* (0.103) | -0.056 (0.047) | -0.002 (0.037) | 0.185 (0.226) | 0.048 (0.040) |
| Log # of other patents | -0.037** (0.017) | -0.037** (0.017) | -0.040** (0.017) | -0.039** (0.018) | -0.038** (0.018) |
| Log sale | -0.047*** (0.005) | -0.046*** (0.005) | -0.045*** (0.005) | -0.046*** (0.005) | -0.046*** (0.005) |
| MTB | -0.003** (0.001) | -0.003** (0.001) | -0.003** (0.001) | -0.003** (0.002) | -0.003** (0.002) |
| ROA | 0.101*** (0.014) | 0.100*** (0.014) | 0.099*** (0.014) | 0.100*** (0.014) | 0.099*** (0.014) |
| R&D | -0.070*** (0.006) | -0.068*** (0.006) | -0.068*** (0.006) | -0.070*** (0.006) | -0.068*** (0.006) |
| R&D missing | -0.152*** (0.030) | -0.149*** (0.030) | -0.147*** (0.030) | -0.148*** (0.030) | -0.150*** (0.030) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| # of AI type k apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| # of other apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 30.45 | 183.28 | 449.37 | 6.43 | 483.57 |
| Observations | 17,391 | 17,376 | 17,414 | 17,395 | 17,380 |
| R-squared | 0.059 | 0.053 | 0.054 | 0.057 | 0.058 |

Table 6. Effects of AI Patents on Skilled Labor Growth: Core and Scope Augmentation

This table reports the second-stage results of 2SLS regression examining the effects of AI innovation on firms' skilled-labor growth through core augmentation and scope augmentation. The endogenous variables and instruments in each regression are as in Table 4. The dependent variable in Panel A (Panel B), *Skilled-labor core (scope) augmentation*, is the net growth of skilled labor in old (new) job roles in the following year. A job role is defined as new if it did not show up in the firm's employment history prior to the most recent three years. Control variables are defined as in Table 3. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for both within-category patents and for all other patents, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| Panel A. Skilled-Labor Core Augmentation | | | | | |
|--|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| | AI Type $k =$ | | | | |
| | <i>Perception</i> | <i>Inference</i> | <i>Prediction</i> | <i>Creativity</i> | <i>Engagement</i> |
| Log # of AI patents of type k | 0.395** (0.155) | -0.101 (0.076) | -0.057 (0.052) | 0.350 (0.317) | 0.180*** (0.052) |
| Log # of other patents | -0.046* (0.025) | -0.044* (0.025) | -0.046* (0.025) | -0.048* (0.025) | -0.050** (0.025) |
| Log sale | -0.061*** (0.008) | -0.060*** (0.008) | -0.061*** (0.008) | -0.060*** (0.008) | -0.060*** (0.008) |
| MTB | 0.005* (0.002) | 0.005* (0.003) | 0.005* (0.003) | 0.005* (0.003) | 0.005* (0.003) |
| ROA | 0.131*** (0.023) | 0.129*** (0.023) | 0.130*** (0.023) | 0.128*** (0.023) | 0.127*** (0.023) |
| R&D | -0.065*** (0.009) | -0.064*** (0.009) | -0.062*** (0.009) | -0.064*** (0.009) | -0.063*** (0.009) |
| R&D missing | -0.181*** (0.043) | -0.181*** (0.042) | -0.178*** (0.042) | -0.173*** (0.043) | -0.178*** (0.042) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| # of AI type k apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| # of other apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 30.45 | 183.28 | 449.37 | 6.43 | 483.57 |
| Observations | 17,391 | 17,376 | 17,414 | 17,395 | 17,380 |
| R-squared | 0.022 | 0.016 | 0.015 | 0.023 | 0.025 |

Table 6, continued

| Panel B. Skilled-Labor Scope Augmentation | | | | | |
|---|----------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| AI Type $k =$ | | | | | |
| | <i>Perception</i> | <i>Inference</i> | <i>Prediction</i> | <i>Creativity</i> | <i>Engagement</i> |
| Log # of AI patents of type k | -0.007 (0.090) | -0.051 (0.035) | -0.006 (0.028) | 0.122 (0.167) | -0.041 (0.031) |
| Log # of other patents | 0.002 (0.019) | 0.002 (0.019) | 0.001 (0.019) | 0.001 (0.019) | 0.003 (0.019) |
| Log sale | -0.019*** (0.005) | -0.019*** (0.005) | -0.018*** (0.005) | -0.018*** (0.005) | -0.019*** (0.005) |
| MTB | -0.007*** (0.002) | -0.007*** (0.002) | -0.008*** (0.002) | -0.007*** (0.002) | -0.008*** (0.002) |
| ROA | 0.011 (0.021) | 0.013 (0.021) | 0.008 (0.021) | 0.013 (0.021) | 0.011 (0.021) |
| R&D | -0.054*** (0.007) | -0.052*** (0.007) | -0.054*** (0.007) | -0.054*** (0.007) | -0.053*** (0.007) |
| R&D missing | -0.132*** (0.030) | -0.128*** (0.030) | -0.128*** (0.030) | -0.129*** (0.029) | -0.130*** (0.029) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| # of AI type k apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| # of other apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 30.45 | 183.28 | 449.37 | 6.43 | 483.57 |
| Observations | 17,391 | 17,376 | 17,414 | 17,395 | 17,380 |
| R-squared | 0.027 | 0.026 | 0.027 | 0.025 | 0.027 |

Table 7. Effects of AI Innovation on Unskilled Labor Growth

This table reports the second-stage results of 2SLS regression examining the effects of AI innovation on firms' unskilled-labor growth. The endogenous variables and instruments in each regression are as in Table 4. The dependent variable, *Unskilled-labor growth*, is a firm's net growth in unskilled labor in the following year. Unskilled labor is defined as the number of employees who hold roles in which fewer than 25 percent of workers have earned at least a bachelor's degree. Control variables are as defined in Table 3. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for both within-category patents and for all other patents, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| | Unskilled Labor Growth | | | | |
|---|------------------------|----------------------|----------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) |
| | AI Type $k =$ | | | | |
| | <i>Perception</i> | <i>Inference</i> | <i>Prediction</i> | <i>Creativity</i> | <i>Engagement</i> |
| Log # of AI patents of type k | -0.029 (0.112) | -0.087* (0.052) | -0.044 (0.040) | 0.059 (0.218) | 0.064* (0.036) |
| Log # of other patents | -0.017 (0.018) | -0.017 (0.018) | -0.019 (0.018) | -0.019 (0.018) | -0.018 (0.018) |
| Log sale | -0.056*** (0.006) | -0.056*** (0.006) | -0.056*** (0.006) | -0.056*** (0.006) | -0.056*** (0.006) |
| MTB | 0.007*** (0.002) | 0.006*** (0.002) | 0.006*** (0.002) | 0.007*** (0.002) | 0.006*** (0.002) |
| ROA | 0.135*** (0.019) | 0.135*** (0.019) | 0.131*** (0.019) | 0.133*** (0.019) | 0.133*** (0.019) |
| R&D | -0.063*** (0.007) | -0.061*** (0.007) | -0.061*** (0.007) | -0.062*** (0.007) | -0.062*** (0.007) |
| R&D missing | -0.151*** (0.034) | -0.146*** (0.034) | -0.148*** (0.034) | -0.144*** (0.034) | -0.146*** (0.033) |
| Firm FEs | Yes | Yes | Yes | Yes | Yes |
| # of AI type k apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| # of other apps \times year FEs | Yes | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 30.45 | 183.28 | 449.37 | 6.43 | 483.57 |
| Observations | 17,391 | 17,376 | 17,414 | 17,395 | 17,380 |
| R-squared | 0.080 | 0.073 | 0.074 | 0.080 | 0.080 |

Table 8. Effects of Augmenting and Displacing AI Innovation on Firm Value

This table reports second-stage results of 2SLS regression examining the effects of AI innovation on firm value. The first-stage regression results are reported in Appendix C, Table C3. *Log # of skilled-labor augmenting (displacing) AI patents* is the log-transformed total number of patent grants which are predicted to augment (displace) a firm's skilled labor, defined based on the regression results in Table 4. *Log # of non-augmenting/displacing AI patents* is the total number of patent grants which are not predicted to be either increase or decrease skilled labor growth. The instruments include the average adjusted patent examiner leniencies for each type of patent application filed by the firm during the year. The dependent variable is the average Tobin's Q over the following two years. Control variables are defined as in Table 3. In Columns (1) and (2), the difference (a)-(b) is the difference in coefficients on *Log # of "type" AI* and *Log # of "other" AI*. In Column (3), the difference (a)-(b) is the difference in coefficients on *Log # of Skilled-labor augmenting AI* and *Log # of Skilled-labor displacing AI*. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for each category of patent application in the regression, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| | (1) | (2) | (3) |
|---|---------------------|-----------|-----------|
| | IV-2SLS (2nd Stage) | | |
| VARIABLES | Tobin's Q | | |
| Log # of Skilled-labor augmenting AI patents | 28.363* | | 34.977** |
| | (15.435) | | (15.934) |
| Log # of Skilled-labor non-augmenting AI patents | -23.361 | | |
| | (18.520) | | |
| Log # of Skilled-labor displacing AI patents | | 1.293 | -16.609 |
| | | (9.908) | (15.034) |
| Log # of Skilled-labor non-displacing AI patents | | -23.149 | |
| | | (18.492) | |
| Log # of Skilled-labor non-augmenting/displacing AI patents | | | -22.942 |
| | | | (18.480) |
| Log sale | -2.765 | -2.859 | -2.710 |
| | (5.987) | (5.994) | (6.005) |
| MTB | 6.159*** | 6.053*** | 6.138*** |
| | (2.195) | (2.188) | (2.198) |
| ROA | -53.560* | -54.410* | -53.878* |
| | (27.760) | (27.910) | (27.841) |
| R&D | -17.163** | -16.767** | -17.447** |
| | (7.179) | (7.139) | (7.206) |
| R&D missing | -42.133 | -41.235 | -42.180 |
| | (26.094) | (25.994) | (26.166) |
| Firm FEs | Yes | Yes | Yes |
| # of augmenting AI apps × year FEs | Yes | | Yes |
| # of non-augmenting AI apps × year FEs | Yes | | |
| # of displacing AI apps × year FEs | | Yes | Yes |
| # of non-displacing AI apps × year FEs | | Yes | |
| # of all other apps × year FEs | | | Yes |
| Kleibergen-Paap F | 73.81 | 341.07 | 66.05 |
| F-stat for test of difference (a)-(b) | 3.99** | 0.93 | 3.11** |
| Observations | 13,770 | 13,771 | 13,741 |
| R-squared | 0.017 | 0.018 | 0.018 |

Table 9. AI Innovation, Firm Value, and Labor Market Competition

This table reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm value in subsamples. Columns (1) and (2) report the results in subsamples of firms with headquarters located in high noncomplete enforceability (*High NCC*) and low noncomplete enforceability (*Low NCC*). A state is defined to have high (low) noncomplete enforceability if its noncomplete enforceability index is above (below) the sample median in a given year. Columns (3) and (4) report the results in subsamples of firms with *More rivals* (number of in-state rival firms is above the sample median during the year) and *Fewer rivals* (in-state rivals below the sample median during the year). The rivals of a given firm (or subsidiary) are measured as the number of non-focal, in-state employees. Any subsidiary-level rivals (from the Revelio Lab database) are aggregated to the parent firm level by taking the average across different states. Other variables of interest are as defined in Table 3. The difference (a)-(b) in all regressions is the difference in coefficients for *Log # of Skilled-labor augmenting AI* and *Log # of Skilled-labor displacing AI*. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for each category of patent application in the regression, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| | (1) | (2) | (3) | (4) |
|--|----------------------|-----------------------|-----------------------|---------------------|
| | IV-2SLS (2nd Stage) | | | |
| VARIABLES | Tobin's Q | | | |
| Sample | High NCC | Low NCC | More rivals | Fewer rivals |
| Log # of Skilled-labor augmenting AI patents | 4.669 (13.193) | 78.569* (46.559) | 85.170* (44.749) | -14.578* (8.245) |
| Log # of Skilled-labor displacing AI patents | 19.148 (12.885) | -80.300** (39.254) | -63.169* (37.720) | 9.699 (11.466) |
| Log # of all other patents | -19.066 (17.669) | -28.227 (32.844) | -25.472 (36.080) | -23.190 (15.608) |
| Log sale | -3.567 (6.006) | -3.335 (12.121) | 2.811 (9.264) | -10.490 (9.742) |
| MTB | 6.747** (3.260) | 5.825* (3.027) | 7.638** (3.419) | 2.610 (1.851) |
| ROA | -29.997 (42.870) | -80.076** (36.794) | -86.208** (39.281) | 19.656 (45.368) |
| R&D | -16.506 (11.726) | -20.959** (8.396) | -32.892** (14.071) | -2.539 (6.622) |
| R&D missing | -65.552* (37.894) | -1.796 (48.924) | -33.130 (60.888) | -6.048 (22.107) |

Table 9, continued

| | | | | |
|---|-------|--------|--------|--------|
| Firm FEs | Yes | Yes | Yes | Yes |
| # of augmenting AI apps \times year FEs | Yes | Yes | Yes | Yes |
| # of displacing AI apps \times year FEs | Yes | Yes | Yes | Yes |
| # of all other apps \times year FEs | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 33.00 | 23.24 | 25.23 | 35.32 |
| F-stats for test of difference (a)-(b) | 0.57 | 3.58** | 3.64** | 1.79 |
| Observations | 7,669 | 5,721 | 6,721 | 6,160 |
| R-squared | 0.015 | 0.026 | 0.034 | -0.001 |

Table 10. AI Innovation, Firm Value, and Labor Protection

This table reports the second-stage results of 2SLS regression examining the effects of AI innovation on firm value in subsamples. The first-stage regression results are reported in Appendix C. Columns (1) and (2) report the results for subsamples where the firm headquarters is located in *RTW passed* (right-to-work law passed) states and *RTW not passed* (right-to-work law not yet or never passed) states, respectively. Columns (3) and (4) report the results for subsamples of firms with headquarters located in *High UI* (unemployment insurance benefits above the sample median during the year) and *Low UI* (unemployment insurance benefits below the sample median during the year) states, respectively. State-level unemployment insurance data are obtained from the U.S. Department of Labor. Unemployment insurance benefits are calculated as the product of average weekly benefits and reciprocity rates of the regular programs. Other variables of interest are as defined in Table 3. The difference (a)-(b) in each regression is the difference in coefficients on *Log # of Skilled-labor augmenting AI* and *Log # of Skilled-labor displacing AI*. Each regression also includes a dummy for missing R&D, application count-by-year fixed effects for each category of patent application in the regression, and firm fixed effects. All continuous variables are winsorized at 1% and 99%. Cluster-robust standard errors are reported in parentheses. *, **, and *** denote significance at 10%, 5%, and 1%.

| | (1) | (2) | (3) | (4) |
|--------------------------------------|----------------------|-----------------------|-----------------------|-----------------------|
| | IV-2SLS (2nd Stage) | | | |
| VARIABLES | Tobin's Q | | | |
| Sample | RTW passed | RTW not passed | High UI | Low UI |
| Log # of Skilled-labor augmenting AI | 151.316 (194.873) | 40.272** (19.388) | 48.432* (25.971) | 27.978 (30.324) |
| Log # of Skilled-labor displacing AI | -39.741 (112.793) | -16.619 (18.964) | -26.631 (26.531) | -69.110** (33.796) |
| Log # of all other patents | 43.131 (29.941) | -43.374* (22.758) | -50.293** (24.882) | 31.690 (37.016) |
| Log sale | -5.301 (15.122) | -2.803 (6.253) | -2.935 (7.816) | -3.517 (12.186) |
| MTB | 9.648 (6.330) | 5.171** (2.013) | 5.605** (2.219) | 3.907 (3.908) |
| ROA | -80.172 (99.798) | -47.971** (22.549) | -57.303* (31.209) | -51.645 (59.829) |
| R&D | -35.622 (33.287) | -14.085*** (4.719) | -13.306** (6.125) | -33.979 (28.874) |
| R&D missing | -118.057 (81.517) | -22.305 (28.266) | -41.877** (20.138) | -40.864 (82.395) |

Table 10, continued

| | | | | |
|---|-------|--------|-------|--------|
| Firm FEs | Yes | Yes | Yes | Yes |
| # of augmenting AI apps \times year FEs | Yes | Yes | Yes | Yes |
| # of displacing AI apps \times year FEs | Yes | Yes | Yes | Yes |
| # of all other apps \times year FEs | Yes | Yes | Yes | Yes |
| Kleibergen-Paap F | 38.74 | 20.48 | 0.98 | 64.08 |
| F-stats for test of difference (a)-(b) | 0.41 | 2.46 | 2.2 | 2.73** |
| Observations | 2,911 | 10,525 | 8,136 | 4,907 |
| R-squared | 0.025 | 0.007 | 0.003 | 0.014 |