Quantifying the Impact of AI on Productivity and Labor Demand: Evidence from U.S. Census Microdata[1]

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Abstract:

After decades of disappointment, artificial intelligence (AI) has entered a new era of rapidly advancing capabilities that are likely to raise productivity and reshape demand for labor within and across firms and industries. Accurately measuring these effects has been difficult due to a lack of detailed, firm-level data on AI innovation. We address that challenge by using a combination of machine learning algorithms to parse the text of U.S. patent grants and assess the degree to which they are AI-related. This approach indicates that AI-related invention is far more pervasive than previous analyses have suggested. We match our data on AI patenting to U.S. Census microdata collected on the innovating firms. We then perform an event study using these matched data to gauge the impact of these innovations on firm labor demand and firm growth. We find that AI-related innovations are positively associated with firm growth as firms with AI-related innovations have 25% faster employment growth and 40% faster revenue growth than a comparative set of firms. We also find evidence that AI-related innovations appear to raise output per worker and increase within-firm wage inequality.

[1] Any opinions and conclusions expressed herein are those of the author(s) and do not necessarily represent the views of the U.S. Census Bureau or the National Bureau of Economic Research. All results have been reviewed to ensure that no confidential information is disclosed. The DRB codes for this project are: DRB-B0027-CED-20190205, CBDRB-FY19-414, and CBDRB-FY20-105.

I. Introduction

After decades of disappointment, artificial intelligence (AI) has entered a new era of rapidly advancing capabilities. The well-publicized recent victories of AI systems over human champions in trivia contests and sophisticated strategy games seem to portend a new era in which human labor will be increasingly supplemented by – and sometimes replaced by – algorithms and machines (Lee, 2018). In the popular media, an increasingly vitriolic debate is being waged between proponents of these new technologies, who believe they will bring a new era of rapid productivity growth and widespread prosperity, and skeptics, who fear an era of mass joblessness and wage stagnation for all but a small cognitive elite (Brynjolfsson and McAfee, 2014).

A measured approach to these questions was taken in a comprehensive study released in 2017 by the National Academies of Science, Engineering, and Medicine entitled Information Technology and the U.S. Workforce: Where Are We and Where Do We Go From Here? (hereafter, NASEM Report). The expert panel authoring this study acknowledged the great promise of AI-related technologies to enhance the productivity of the economy, but also noted the real possibility that particular occupations, industries, and groups of workers could experience significant disruption in the short run. However, the experts noted that reliable forecasts of these effects are powerfully undermined by the absence of good data on the deployment of AI in the economy.

Existing Indicators Cannot Track the Movement of AI into the Marketplace

The NASEM Report emphasized the central importance of better measures of the development and diffusion of potentially disruptive new technologies associated with artificial intelligence and machine learning. Existing official science and technology indicators are far too crude to trace the development of these technologies and track their deployment in actual goods and services. This poses a fundamental challenge for public policies that might seek to ameliorate the disruptive impact these technologies are likely to have on the U.S. labor market – one cannot target what one cannot see. It also limits our ability to quantify the degree to which AI is living up to its promise of faster economic growth and higher productivity. While industry advocates have triumphantly proclaimed the advent of a fourth industrial revolution (4IR), our admittedly backward-looking aggregate productivity statistics suggest that productivity growth has been stuck in low gear since before the global financial crisis of 2008-2009, and remains well below long-run average levels (Byrne et al., 2016). Since accelerated productivity growth is the hallmark of a real industrial revolution, the aggregate statistics raise the concern that hype has gotten far ahead of reality. On the other hand, AI is only now emerging as a significant innovation driver, and it is entirely possible that aggregate statistics are missing or obscuring the positive impact that AI is already having on early-adopting firms and industries. Without better data, it is impossible to distinguish empirically between these two views.

The Solution: Patent Data as an AI Innovation Indicator

Fortunately, there is a heretofore underutilized source of data to which we can turn. Firms that succeed in using artificial intelligence to create new goods and services have a strong incentive to patent at least some of their inventions. If they fail to do so, other firms can copy their innovations without penalty or use patents to block the original innovator from applying their inventions in the marketplace. This means that firms throughout world are filing thousands of AI-related patents with the U.S. Patent and Trademark Office (Cockburn et al., 2019; Webb et al., 2019). By law, the vast majority of patent documents become public 18 months after filing, even if they are still being adjudicated by the patent office. Each patent application is supposed to provide sufficient detail such that the invention could be replicated by an individual who is proficient in the technology.

Patents are classified according to the technology they contain, and the U.S. Patent and Trademark Office has created a detailed taxonomy containing several hundred patent classes (and thousands of subclasses). However, if we only count patents in those classes and subclasses specifically and primarily associated with "artificial intelligence," we may vastly undercount the true scope and scale of AI-related invention. The reason a narrow focus is insufficient is precisely the reason that this emerging technology is so important – the applications, current and potential, of artificial intelligence, machine learning, "big data," and AI are so broad as to encompass virtually the entire economy. Similar machine learning algorithms can be used in combines, cars, jets, banks, insurance companies, and travel agencies, and the patents that apply them to these different domains could show up across a vast range of classes, including classes associated with the domain of application of the patent, such as patent classes traditionally associated with tractors and combines. A patent search procedure that examined only patents in the USTPO's designated patent class for artificial intelligence or focused only on a handful of key words will miss far more than it captures. Our results to date show this to be the case, and we demonstrate that in the next section.

Fortunately, modern developments in natural language processing permit a different approach. By training machine learning algorithms to parse the full text of patent documents, we can, in principle, capture nearly all AI-related inventions, regardless of the patent class to which they may be assigned by patent examiners. This gives us a broader, more complete data window through which to view the rise of AI-related invention. Our research team created an algorithm that can quickly sort through millions of patents, assigning each to an appropriate AI-related bin, or not, as the text of the patent dictates. Our paper describes, in some detail, the creation and training of this algorithm.

Once we have correctly identified AI-related patents, we possess a highly granular map of AI invention that identifies the corporate owners of the patents, the geographic location of the inventors who created the new technology, and the time when the invention was originally conceived. We can thus trace AI-invention across time, geographic space, and industry space, and identify the firms that are most active in creating inventions in this new domain. We present some of the interesting findings one can infer from tabulations of the raw data in this map and quantify the impact of AI on American invention, labor demand, firm productivity, and other key variables.

Mapping to Census

In fulfillment of its institutional mission, the U.S. Census Bureau (hereafter Census) maintains detailed data on U.S. enterprises, including privately held enterprises that make few public disclosures about their business operations. Furthermore, the data collected by Census provides additional details that go beyond what publicly traded firms are required to disclose. For instance, Census gathers data not only on firms but also on the establishments – the individual business units – created by these firms, with identifiers that link them all to the parent firm; these data track mergers, acquisitions, and divestitures, ensuring that the mapping from parent firms to establishments remains current. Among other things, Census surveys establishments on their output (broken down by industry), material inputs, capital investment, and employment. For the manufacturing sector, Census has invested in a detailed mapping that connects the patent owners (assignees) listed in USPTO patent data records to their own firm identification codes, adjusting for mergers and acquisitions.[2] This allows us to match data on the creation of AI technology by individual firms to the possible impact of that technology on their productivity growth. This, in turn, allows us to infer the impact of AI-invention on productivity. Our data, linking tens of thousands of AI-related patents to thousands of firms, are rich enough that we can explore the potential heterogeneity of this impact across time, industries, and firms of different types. Some observers worry that AI technologies will create a kind of winner-take-all industry dynamic, in which the benefits of the technology accrue to a small number of firms that implement it first. We can directly address this concern, establishing whether the productivity impact of AI invention is concentrated in a handful of leading firms or more broadly observed. In this way, we can determine to what extent AI is fulfilling the promise of enhanced productivity predicted by its proponents.

II. Artificial Intelligence as a General Purpose Technology

Leading consulting firms (McKinsey Global Institute, 2016), leading academics (Brynjolfsson and McAfee, 2014), and leading CEOs have all claimed that industrial firms have now entered a new era, enabled by AI and related technologies, that can fundamentally transform business across the economy. If we translate the enthusiasm of these proponents into the language of economics, they are essentially contending that rise of AI constitutes the emergence of a new "general purpose technology" (GPT). The economic literature on general purpose technologies (Bresnahan and Trajtenberg, 1995; Helpman, 1998) can be useful in helping us think about the impact of all this as a new technology of technological change. The confluence of AI-related technologies that has opened up these new opportunities are broadly applicable, potentially touching nearly every industry in the global economy. But every effective application of this suite of new technologies requires product and industry-specific knowledge, embodied in the software and hardware that makes these general purpose technologies work in fundamentally different contexts. So, every industry and firm needs to invest in new technology and new capabilities. This suggests the possibility of inferring the impact of AI on the direction and pace of inventive activity in the U.S. by using patent data.

[2] A mapping also exists for services firms, but is less complete.

Precisely because the potential impact of AI is so broad, and the need for complementary innovation to adapt it to the vast array of contexts in which it can be applied is so great, it may take time for this impact to manifest itself in aggregate statistics. As David (1991) pointed out in his famous comparison of electricity and IT, the basic inventions necessary for the electrification of U.S. manufacturing were created decades before they were widely applied. Eventually, this process resulted in a significant and persistent surge in U.S. productivity growth. Of course, some firms and industries were in the vanguard of the process of electrification of manufacturing processes, achieving important gains years or even decades before other firms and industries.

The publication in 2019 of *The Economics of Artificial Intelligence: An Agenda* represents an important step forward in economists' investigation of this important technological shift. Several chapters in this volume take the view that AI is a general purpose technology, and explore that idea in a number of different ways. Agrawal, Gans, and Goldfarb (2019) advance the idea that AI algorithms are "prediction machines," enabling agents throughout the economy to better forecast outcomes, reducing uncertainty in a range of economic tasks. Agrawal, McHale, and Oettl (2019) suggest an important application of this idea, in terms of enabling firms to find productive new combinations of existing technologies. Cockburn et al. (2019) also view AI as a new technology for invention. However, a number of chapters in the volume point to the wide range of unanswered questions, and Raj and Seamans (2019), in particular, emphasize the importance of more firm-level data on AI invention, AI adoption, and its effects.

We seek to address this lack of firm-level data, by using patent to detect AI invention and then linking data on patenting to the rich microdata maintained by Census on the innovating firms. In doing so, we build on the work of other researchers that are also using patents as an indicator of AI invention and deployment, including Cockburn et al., 2019, and Webb et al., 2019. However, our approach to the identification of AI-related patents differs substantially from that of these other researchers. These prior studies follow earlier investigations by economists in using a small number of patent classes and a small number of keywords to identify relevant patents. We argue below that this conservative approach probably misses a very large number of AI-related inventions whose patents do not incorporate exactly these key words or fall in the designated classes. Precisely because of its "GPT" nature, AI-related inventions are likely to fall across a wide range of classes and use a wide range of terms and descriptions. So, we use the interactive training procedure described below to train a suite of machine learning algorithms to identify AI-related patents, eliminating the need to preselect all of the necessary key words, phrases, or classes. Our classifier algorithms not only indicate whether a particular patent is AI-related or not, it also provides us a univariate measure of an individual patents "AI-ness," so that we can experiment with narrower and broader definitions. As the reader will see, our approach identifies far more AI patents than the papers noted above. Whereas Cockburn et al. (2019) identify fewer than 14,000 AI patents, our approach, utilized over a slightly longer data window, identifies more than 52,000 using our most stringent definition and more than 140,000 using a looser, but still reasonable definition. This is an order of magnitude larger than the set of AI patents identified by more conventional techniques.

III. Using Machine Learning Techniques to Identify AI Patents

a. Identifying AI Patents

Our goal is to construct a large dataset of AI-related and non AI-related patents in order to train a robust machine learning model that can identify AI innovation across a wide range of invention domains. A natural approach to this task would be to leverage a schema such as the US Patent Classification (USPC), International Patent Classification (IPC) or Cooperative Patent Classification (CPC) systems, which have categories for different types of AI-related innovations. The World Intellectual Property Organization and other patent offices employ machine learning models to assign patent application to IPC classifications. (WIPO 2019) Other researchers have taken various machine learning approaches to emulating IPC classification. (Benites et. Al 2018; Grawe et. Al 2017). However, in practice this results in a few challenges. These classification systems use a deep, multi-label taxonomy in which a single patent can be assigned to multiple categories. The nebulous concept of AI is therefore captured using several non-overlapping classification labels. Unfortunately, this classification system is not perfect, with many inventions that describe intelligent technologies falling outside of the explicit AI categories in these systems, or assigned to categories in which there is a mix of both AI and non-AI inventions. Likewise, some inventions that leverage AI technologies as a component in a larger invention may not be assigned to an AI classification at all. These limitations are inherent in utilizing a patent classification system to study commercial activity. As noted by Jaffe, existing patent classification systems are designed by patent offices to locate "prior art" for patent applications under examination. Such classification systems are not a substitute for product or industry classification, and "the mapping from classes to industries is not unique in either direction". (Jaffe 1986).

Much prior work in this area has also leveraged keyword-matching methods to identify patents that describe the use of particular algorithms, techniques, or areas of AI research. These methods achieve high precision in identifying AI patents, but suffer from low recall and find only a small fraction of the total patents leveraging AI technologies. For example, a component in an invention might be described as a model trained on a particular kind of data, without specifying the type of model in order to avoid restricting the scope of the patent. These inventions often clearly describe AI-related technologies, but do so without easily identifiable keywords, resulting in them being left out of these approaches. This is again common in inventions in which the AI component is only a part of the greater invention, as opposed to the core proposed innovation.

Training a model using patents labeled automatically by either of these methods could therefore result in a model that is highly biased towards particular phrases, or towards certain subfields of AI innovation. We instead adopt a manual annotation approach, identifying patents that describe or utilize AI technologies with a focus on covering a wide range of different applications and domains.

The next several subsections of the paper provide some important details on our use of natural language processing (NLP) and machine learning (ML) techniques to build the patent dataset. It includes terms and descriptions that may be unfamiliar to readers who have not studied the language processing techniques now widely used in computer science. In future versions of the paper, we hope to provide additional text that will make the following sections more fully accessible for economists and other social scientists.

b. Dataset Construction

We construct our dataset using a semi-supervised iterative approach, in which we train a machine learning model to identify AI patents and then apply it to the full USPTO patent corpus from 1990-2018. We then manually review selections at different decision thresholds, which can help us quickly find and validate high confidence AI and non-AI patents for our dataset, as well as find and more carefully review patents that the model predicted with lower confidence. We start with an initial set of 330 patents that had been manually identified as AI-related under a previous effort. For our initial model, we augment this dataset with patents from class 706, the artificial intelligence category, in the U.S. patent classification system to serve as the positive class, and select the negative class from all other categories in the system, excluding a few other AI-related categories. For this initial step, we train a simple decision tree model on a tf.idf weighted bag of words representation of the claims sections of the patent and extract the term features used by the model. We retrieve a ranked list of patents from a Lucene-based text index using these keywords and then label 50-100 documents at several points through the ranked list using the labeling process described in the previous section. This allows us to quickly find 1) AI patents that don't have these keywords and thus appear lower in the list and 2) non-AI patents that ranked highly in the list, therefore helping us expand our AI and non-AI sets beyond what keyword matching might have identified.

At the end of this first phase, we have a set of 1,200 evenly split AI and non-AI patents, which we now use to train a Support Vector Machine (SVM) model (Cortes and Vapnik, 1995). We applied the trained model to the full artificial intelligence class of the U.S. patent classification system and ranked them by how likely they were to be AI patents according to the model. We vet the highest confidence decisions, using a quicker process to verify the model's predictions, and more carefully review 350 low confidence predictions by the model. After this second phase, we have a set of 2,000 patents, evenly split between AI and non-AI which we can use to run a greater set of experiments.

c. Classification

We train and apply several alternative classifiers to label each patent as "AI" or "non-AI". We compare the performance of these modules by measuring their F1 scores on a held-out test set of patents. The classifiers implement two types of machine learning: statistical and neural.

We split the set of 2,000 patents (1000 each AI and non-AI) into three subsets: assigning 10% for validation, 10% for evaluation, and 80% for training, maintaining even numbers of AI and non-AI patents in all sets.

d. Statistical Models

Using the text from each patent's Abstract, Claims, and Description fields, we represent the patent as a bag-of-words vector with tf.idf weight scores. We train the following statistical machine learning models using the Python scikit-learn toolkit: 1) Naïve Bayes, 2) logistic regression, 3) random forest (Ho, 1995), and 4) linear support vector machine. We tune the hyperparameters for each model using three-fold cross-validation (in which 1/3 of the data is held out as a validation set while the model is trained on the remaining two thirds), and average performance scores across the three trained models to determine the best parameters.

e. Neural Models

We implement three neural classification models in addition to the above models. As before, we use the text of the Abstract, Claims, and Description fields only. We use the fastText toolkit built by Facebook (https://en.wikipedia.org/wiki/FastText) to build skipgram word embeddings (Mikolov et al. 2013) on the text of all patents from 1990–2018. (Doing so provides word embeddings tailored specifically to the language of patents.) These embeddings are the first layer in all our neural models that form vectors for use in later layers. In each neural model, the embeddings forming the input text are converted via several layers in the neural network to a final AI or Non-AI decision. We apply our three neural transformation architectures separately to each of the three patent sections, and at the end concatenate the final representations for the three sections together to obtain a final representation of the document, which is then used by the final classifier to predict whether the document is AI or not.

Convolutional neural network (CNN): A convolutional neural network, also called a time-delay neural network (Waibel et al. 1989) applies a sliding window left-to-right over the text to extract local patterns that may be useful for classification. After traversing the whole sequence of text, we pool the extracted features using a max pooling layer to obtain a single vector, which is then used for the final classification decision. We use multiple convolutional layers concurrently with different sliding window sizes, or kernel widths, in order to extract patterns of varying lengths, and concatenate the final representations together for each section of the patent.

Recurrent neural network (RNN): An RNN model (Rumelhart et al. 1988) applies a function sequentially to a series of input word embeddings, and includes a mechanism to allow the model to retain information encountered early in the sequence for later application. The function outputs a vector after reading each input word, and after processing the whole sequence we again use a max pooling function to combine all the outputs into a single vector representation. We apply a single recurrent layer in both directions over the text using a Gated Recurrent Unit (GRU) (Cho et al. 2014). We concatenate the final outputs in both directions to create the final vector representation for the classification decision.

Hierarchical attention network (HAN) (Yang et al. 2016): The model proceeds 'top-down', breaking the patent down into sentences, and subsequently words. For each sentence, a recurrent layer is passed over its word embeddings and the outputs for the words are combined using an attention layer. This network layer allows the model to dynamically weight each of the outputs from the recurrent function, essentially allowing the model to decide how important each word in the input is. The weighted outputs are then summed to create a single representation for the sentence, which is passed to the final classification decision.

We tune the hyperparameters of our neural models using ten-fold cross-validation and generate predictions by taking the average of the predictions for the ten trained models.

f. Model Performance and Comparison

Table 1 Statistical and neural model performance on AI patent classification

Model	Test Micro F1
Naïve Bayes	.765
Logistic Regression	.885
Random Forest	.910
Linear SVM	.890
CNN	.901
RNN	.905
HAN	.911

Evaluation performance of each model is shown in Table 1, using the F1 score, which weights Precision (accuracy) and Recall (coverage) equally. Average model performance is fairly strong on the evaluation set, ranging from .81 to .91 F1 across the various different model architectures.

However, the predicted likelihood that any given document is AI can widely vary across the different models, so we use these differences to identify areas where our models may be overfitting to the data due to the data size. For each pair of models, we identify the 25–30 documents with the largest differences in model prediction scores. These indicate documents that may be very challenging for one of the models and therefore might most benefit from further manual review. We collect a set of 328 patents and manually review them, creating a small "challenge" set which will help indicate how well any model is generalizing to a set of challenging sub-areas. While in some cases we find examples that indicate strong overfitting to particular terms, such as "training" or "network", many documents in the challenge set come from conceptually similar technology areas that would be difficult to classify as AI or Non-AI even for humans. These include particular algorithm formulations that resemble rule-based AI systems, patents that contain boilerplate language about how an invention may incorporate statistical modeling components, and certain image processing techniques commonly used as inputs to more advanced AI systems that in themselves might be considered not-AI.

g. Model Ensembling

It is fairly common to obtain better and more stable classification performance by merging (ensembling) the results of classifiers built on different principles. Using the above challenge set, we combine the various model architectures to create a more robust model ensemble. For each model pair from the challenge set selection step, we assign a portion of the labeled documents for that pair to either a new training, validation, or test set. We further supplement these new sets with documents from the original training and evaluation sets. For the evaluation set, we use the entire original evaluation set, creating a new evaluation set with 298 documents. For the validation set, we use 50 each of AI and non-AI labeled documents from the original training set. Finally we add the rest of the original training set (1700 documents) to the challenge set documents to construct the ensemble training set.

As inputs to the ensemble model, we use both the tf.idf bag-of-words representation (used by the statistical models) and the AI likelihood scores produced by each trained model. In addition we use one feature for each statistical model and eleven features for each neural model (namely the predictions from each of the ten cross-fold models plus their average). For the ensemble models, we experiment with a random forest, a support vector machine using an RBF kernel, and logistic regression, tuning the parameters for the models on the validation set.

We report micro F1 statistics on the validation and test sets in Table 2. We show results on our challenge-augmented datasets using the model ensemble features as well as just using the tf.idf representation of the patents. The ensemble features produce large performance increases: 0.7–6.0 F1 scores on the validation set and 4.3–8.0 F1 scores on the test set. The more-varied representations learned by the different models therefore prove to be quite valuable in discerning between the more challenging documents in these sets.

Table 2: Validation and Tests of Various ML models

Model	Features	Validation Micro F1	Test Micro F1
Logistic Regression	TFIDF	.887	.792
Logistic Regression	TFIDF+Ensemble	.908	.872
Random Forest	TFIDF	.901	.839
Random Forest	TFIDF+Ensemble	.908	.886
SVM	TFIDF	.873	.819
SVM	TFIDF+Ensemble	.937	.862

Using the random forest model, we label all patents granted by the USPTO between 1990–2018 and define two sets based on prediction score thresholds at 0.7 and 0.95. These contain 146,952 and 52,896 patents respectively, and are listed below. A full representation of the machine learning process to identify the AI patents is given in Figure 1.

IV. Mapping AI Invention in Geographic Space and Time

Our methodology yields a large number of patents originating from many different technological fields. We highlight some of the interesting patterns in the data before we begin our econometric analysis of the matched patent-census data set.

We start by noting the counts of AI patents over our time period. Figure 2 plots the growth of AI patents found in the set of USPTO data. The blue bar represent the counts with 70% confidence, while the orange bar represents the counts with 95% confidence. For the purposes of our analysis, we will predominantly focus on the latter (95% confidence). The number of AI-related innovations increased dramatically between 2000 and 2018. In 2000, there were 539 AI-related patents granted (95% confidence) and this number increased to more than 6,300 in 2018.

We can utilize the geographic data for the assignees or inventors of these patents to chart the origination of these patents. A number of well-known experts have raised the concern that the U.S. is now lagging behind other countries, especially China, in terms of research investments in AI (Lee, 2018). Figure 3 assigns a geographic location to each patent, based on the location of its inventors. Since we are using patents granted by the USPTO, these data will have a well-documented U.S. bias, since inventors tend to take out patents in their home market first and patent selectively abroad. However, even allowing for this bias, the overwhelming dominance of U.S. inventors in the AI space is striking. Conversely, the tiny numbers of AI patents ascribed to mainland Chinese inventors is equally striking. Our data identify more AI patents created by Taiwanese inventors than on the Chinese mainland. Given the enormous size of the U.S. economy – still larger than China's at market exchange rates by a conventional measure – and the highly developed nature of the AI economy within the U.S., if Chinese inventors have valuable new technology that they eventually wish to deploy abroad, they would seem to be running a nontrivial risk in not patenting that technology in the U.S. These data do not support the notion that the U.S. is falling behind in AI invention.,

In addition to the country codes of the assignees, we can utilize the geographic data of the inventors to plot where in the U.S. the AI-related innovations are taking place. This picture is rendered in Figure 4. Perhaps unsurprisingly, we find that AI patenting activity is concentrated in the high-tech areas of Silicon Valley, Seattle, Austin, and New York.

Finally, we can plot the technology classes that have seen the most activity in terms of AI. Figure 5 plots the 25 most common USPC codes found on the patents of AI innovations. The most common USPC codes consist of 382, Image Analysis, and Data Processing (USPC 702 – 709). However, it is clear from this graph that AI patents appear to be widely distributed across a very large number of patent classes, with patents applying AI to particular domains showing up in the classes associated with those domains of application. This is, perhaps, what we would expect if AI truly is a general purpose technology, and these findings lend support to our methodology for the identification of the patents.

In order to gain a better understanding of how AI is impacting the larger economy, it is necessary to link the AI patents and accompanying assignees with data on firm performance. We can do this through an existing mapping between U.S. patents granted to U.S. firms and detailed firm-level data housed at the U.S. Census Bureau. The steps for creating this linkage is described below.

V. AI Invention at the Firm Level

a. Linking Patents to Firms Using the Patent to Census Crosswalk

Once the patents have been identified, we can link the U.S. assignees of these innovations to firm-level microdata using an existing USPTO Patent to Census Crosswalk first generated by

Graham et al. (2018). This crosswalk builds upon previous efforts by Kerr & Fu (2008) and Balasubramanian & Sivadasan (2011) that have linked the NBER patent database to Census data. In the Graham et al. (2018) approach, the authors bring in the full USPTO database from PatentsView and incorporate a triangulation approach that combines fuzzy name and address matching of the assignee with the firm name and address found in the Census Business Register (BR), and inventor links in the Longitudinal Employer Household Dynamics (LEHD) data, that matches employees with their employers. The resulting crosswalk improves upon previous efforts to link patent data with Census data that relied solely on the assignee matches. The inventor links are used to disambiguate many-to-one firm-level matches and thus provide a cleaner and more accurate linkage then previous efforts. However, this precision comes at a cost, as the inventor links are primarily available after 2000.[3]

The result of this crosswalk is a patent-to-Census firm identifier for all U.S. patents granted between 2000 and 2016. Using this crosswalk, we are able to link approximately 65% of AI-related innovations.[4] The somewhat low match-rate is the result of foreign assignees, as well as patents that fall outside of the time range of the crosswalk (patent grant dates between 2000 and 2016). When we limit the set of AI-innovations to U.S. assignees granted between 2000 and 2016, the match rate is around 90%. The resulting set of firms and their AI innovations form the basis of the analysis described below.

In addition to the firm-level data across various Census datasets, we also incorporate worker-level data from the LEHD to construct our measures of earnings ratios. The LEHD provides us with quarterly earnings data compiled from state unemployment insurance (UI) wage records and the Quarterly Census of Employment and Wages (QCEW) data (see Abowd et al. (2009) for notes on the construction and source files)). The coverage of this data is broad (roughly 98% of private sector employers submit wage records), but state level participation has varied over time with approximately 20 states participating in the start of our analysis (1997), with that number climbing to 49 states by the conclusion).

The firm links from the USPTO match are able to identify the set of workers and their corresponding earnings in each quarter. These earnings consist of traditional hourly or salary earnings, along with bonuses and other potentially irregular large payments (including income derived from the exercise of stock options by employees at high-tech AI-inventing firms). To counteract these irregular payments, we winsorize the earnings distribution at 99 percent of the state-year-quarter distribution (approximately $125,000 per quarter on average). We also only keep the “full-quarter” earnings of workers (defined as being employed in the previous quarter and the following quarter) and to construct the annual measures of earnings ratio for each firm, we first construct the earnings ratio and then take the four quarter average.

3 We can link some of the patents granted prior to 2000 to Census data using the assignee-to-firm matches gathered in the post-2000 era. For AI patents granted before 2000, the non-matches primarily occur with assignees who did not take out any additional AI patents post-2000.

4 Our match rate is somewhat lower than expected mainly due to the timing of the AI-related innovations that fall outside the range of the USPTO-to-Census crosswalk. AI patents granted prior to 2000 or after 2016 are not matched. When we limit the set of patents to U.S. assignees with a grant date between 2000 and 2016, our match rate is ~90%.

b. The Characteristics of AI-Inventing Firms

Before delving into our analysis, it may be helpful to review the types of firms that are innovating in AI and how they might differ from the typical manufacturing firm, or even typical innovating firm. We categorize each firm as follows and compare their 2016 firm characteristics. For firms with at least 1 patent in their portfolio, these firms are classified as patenting firms, while firms with at least 1 AI patent (95% confidence) are categorized as an AI firm. Table 3 compares their baseline characteristics in 2016.

Table 3: Summary Statistics by Firm Type, 2016

Variable	**ALL US FIRMS**	**PATENTING FIRMS**	**FIRMS WITH AI PATENT**
Mean Employment	32	1,890	18,200
Mean Age	13.5	24.3	26.2
Mean Payroll per Employee	$40,200	$77,500	$111,100
% Multi-unit	3.1%	33.3%	60.0%
% Multinational	1.4%	32.6%	50.5%
Observations	6,270,000	27,000	1,200

The first thing to notice is how much larger firms with AI patents are relative to their counterparts. Firms with patents are nearly 60x larger than the average U.S. firm, while firms with at least 1 AI patent are nearly 600x times larger. Innovating firms are also significantly older on average, more capitalized (pay higher earnings per employee), much more likely to be multi-unit and multinational.

Looking at the distribution of these same statistics, the differences are just as stark. Figure 6 plots the Kernel density (Gaussian) for size and earnings across the 3 firm types in 2016 and then looks at the distribution of value-added per worker, production worker share, total factor productivity (TFP) and capital-labor ratio for the set of manufacturing firms within each sample. We can see that the distribution of employment across the firm types systematically differ as the majority of U.S. firms tend to be relatively small. Patenting firms have a more normalized distribution, with a slightly fatter tail, while firms with AI patents are primarily concentrated in large firms (firms with 1000+ employees). In the distribution of payroll per employee, we find that the distribution across all firms is normal, with lowest variability and highest means in firms with AI patents. This same pattern persists in our measure of productivity for manufacturing firms (value-added per employee), as well as across different measures of productivity (TFP). All firm types follow a normal distribution, with AI-patenting firms having the highest average and lowest variability. Our capital-labor ratios also show that firms with AI patents tend to have higher capital-labor ratios.

Our measure of production worker share is intended to capture the labor demand across the different firm types, with production workers typically being classified as lower skilled. Our density plots reveal somewhat inconsistent patterns as patenting firms tend to have the highest share of production workers (relative to total employment), while firms with AI patents have the lowest share.

To summarize, firms with AI patents differ across a number of important dimensions from the typical U.S. firm and from innovating firms (defined as firms with patents). They are on average much larger, older, better capitalized, more productive and significantly more likely to be multinational and multi-unit. They also employ fewer lower skilled workers on average. The next section describes how we estimate the impact of AI on both productivity and labor demand.

VI. Estimating the Impact of AI on Productivity and Labor Demand

The next section describes our methodology for assessing the impact of AI innovations on productivity and labor demand. This section is mainly descriptive as the decision to innovate in artificial intelligence is likely to be endogenous with other firm decisions that could potentially impact the outcomes that we are measuring. In the previous section, we demonstrated that the firms that invest in AI-related innovations are categorically different from the vast majority of firms in our data. These differences are unlikely to result entirely from the decision to innovate in AI, but are due to a combination of several factors, many of which are related. Thus, while our language may, in places, suggest a causal relationship between AI invention and other variables of interest, we are not, at this point, making any strong claims about causality.

We first take a standard approach, using the advent of AI as our treatment and employing simple linear regression models to measure the impact of this treatment on four separate outcomes: employment, revenue per employee, value-added per employee and production worker share. Our sample of firms in this traditional approach is the entire set of manufacturing firms in the U.S. between 1997 and 2012. In these regressions, we make no effort to "match" our AI firms with firms that are very similar in observable characteristics, but do not create AI patents.

Our second approach attempts to partially control for endogeneity and confounding factors that we cannot measure in the data by matching each firm in our set of AI-inventing firms with a closely-related counterpart that has not generated AI patents. We then measure the before and after effects of the AI patent. In both approaches, we find that AI innovations are positively and significantly associated with higher employment, more revenue per employee, greater value-added per employee and fewer production workers (lower-skilled labor). We also find that the strength of this treatment grows in the years following the initial innovation, with employment being approximately 25% higher and revenue being 40% higher five years after treatment.

a. Standard Linear Regression Approaches

a.1 Revenue per Worker and Value Added

If AI is dramatically raising the productivity of invention, than it should lead not only to more patents but also higher levels of revenue, by increasing product quality, and thus product demand, or lowering production costs. Our approach to the measurement of these effects can be motivated by a standard Cobb-Douglas production function, in which counts of AI patents or a dummy variable equal to 1 when AI patenting begins are introduced as a separate regressor. Thus, suppressing time subscripts, output can be described as:

$$Q_i = K_i^{\alpha} L_i^{\beta} A_i^{\varphi} e^{\varepsilon_i}$$

taking the logs of both sides and normalizing output by employment gives us

$$q_i - l_i = \alpha + \varphi a_i + \varepsilon_i$$

Here *q* is output, *k* is capital, *l* is labor input, and *a* is the firm-level measure of AI innovation. In future versions of the paper, we will include R&D as a regressor, but note that the sample of firms will significantly decline with its inclusion due to selection (see Foster, Grim and Zolas (2019)). For now, we allow for the existence of individual effects which are potentially correlated with right hand side regressors, such that

$$\varepsilon_{it} = \lambda_{it} + u_i$$

The standard procedure is, to use a "within" panel estimator to eliminate the individual effect, which is what we do.[5] The coefficient of interest, φ, picks up the effect of changes in firm *i*'s own AI intensity on its productivity or outcome variable. Our primary outcome measures will be revenue per employee and value-added per employee. Our firm controls include the firm's capital stock, multinational status, age, as well as individual and yearly fixed effects.

Our primary variable of interest is an indicator variable (1/0) showing whether the firm has obtained at least one AI patent or not. When incorporating firm fixed effects, our identification hinges on firms which transition into AI innovation over our time period, 1997-2016. The results from our initial specification can be found in Table 4 below.

[5] However, if there is measurement error in the variables of interest, the "within" estimate may have a serious bias of its own, in which case, we would want to follow Griliches and Hausman (1986), who use a "within" estimator that is less likely to suffer from this second source of bias than either using the first-differences estimator or transforming the data by calculating deviations from firms' "time means." In later versions of the paper, we will use the so-called "long difference" estimator, regressing the log difference in the starting and ending levels of firms' sales on the "long" log difference in levels of capital and labor inputs, etc. With this specification, our estimates should be consistent in the presence of measurement error as well as individual effects which are correlated with firm's levels of capital, employment, R&D and AI innovation.

Table 4: Impact of AI Innovations on Firm Productivity, 1997-2016 (manufacturing firms only)

	Ln Total Value of Shipments per Employee	Ln Value Added Per Employee	Ln Total Factor Productivity (TFP)
AI Treatment (1/0)	0.0836***	0.0890***	0.0700***
	(0.0198)	(0.0228)	(0.0169)
Ln Capital Stock	0.269***	0.257***	
	(0.000963)	(0.00111)	
Age	-0.107***	-0.113***	0.00663**
	(0.00205)	(0.00236)	(0.00212)
Multinational Status (1/0)	-0.0772***	-0.0846***	-0.00337
	(0.00256)	(0.00294)	(0.00214)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,614,000	1,614,000	1,614,000
R-squared	0.910	0.892	0.724

Robust Standard Errors clustered at the 4-digit NAICS industry level. *, ** and *** denotes significance at the 5%, 1% and 0.1% respectively. Each regression includes a constant, which is not displayed here. Note that our Multi-Unit regressor drops out from the within-firm specification as the firm-identifier for multi-unit status does not change. Across firm effects are available on request.

Taking our standard linear approach, we find that the presence of AI patents among manufacturing firms has a positive and significant effect on both revenue per employee and value-added per employee. According to the coefficient value, an AI patent is associated with an 8.3% increase in total value of sales (revenue) per employee, an 8.9% increase in value-added per employee and 7% increase in TFP. These results are within-firm and it should be noted that the across-firm estimates are significantly higher. The next section describes our method for estimating the changes to labor demand.

a.2 Labor Demand

Matching firm-level data on AI patenting to firm-level data on employment allows us to make potentially significant contributions to the current understanding of the impact of AI on the labor market. Due to the lack of firm-level data, much prior research has used textual descriptions of the task content of various occupations and information on the emerging capabilities of AI algorithms to “predict” the possible impact of AI on employment (e.g., Brynjolfsson, Mitchell, and Rock, 2018). We find this line of research useful, but because it is not based on actual observations of real firms altering their labor demand as they create and deploy AI technology within the firm, this line of research is necessarily speculative. In contrast, our unique data match allows us explore how leading firms adjust their employment as they create AI technology.

A long tradition in labor economics and international trade exploits the fact that most production workers are relatively less skilled, and most nonproduction workers relatively more skilled so that changes in the ratio of production to nonproduction workers can serve as a proxy measure for skill-bias in labor demand (e.g., Berman, Bound, and Griliches, 1994). Building on this literature, the results below, while limited, point to an interesting, complex, and possibly nonlinear relationship between AI invention and demand for less-skilled workers. The results appear to strengthen when we focus on a propensity score matched sample.

As noted in our introduction, one of the most salient controversies surrounding AI is its potential impact on wage inequality. A large literature in labor economics documents the impact of earlier generations of information technology on the relative demand for skilled labor (Autor et al., 1998; Autor et al., 2003). As earlier waves of automation and computerization advanced, a large body of evidence suggests that demand for the most skilled workers increased but demand for the less skilled workers decreased, accounting for a significant degree of the rise in income inequality that has characterized U.S. labor markets since the 1970s.[6] Many observers worry that AI will continue, and perhaps even exacerbate these longstanding trends.

As we noted in our introduction, the richness of our data enables us to probe for the existence of these effects at the level of the firm. One empirically feasible approach is to estimate an equation along the lines of Berman, Bound, and Griliches (1994), who derived an equation explaining the nonproduction worker share of total employment in manufacturing industries as a function of relative wages, capital intensity, and a series of additional variables proxying for skill-biased technological change, including industry-level measures of R&D and computer investment. Following their logic, we can use firm-level data from Census to estimate an equation along the lines of:

$$dS_i = \beta_0 + \beta_1 dln(K_i/Y_i) + \beta_2 dln(A_i) + \varepsilon_i$$

where S measures changes in the nonproduction worker share of firm i over some period of time, modeled as a function of changes in the capital intensity of firm i, (K_{it}/Y_{it}), and a measure of changes in the AI-intensity of firm innovation, A_{it}, over the same time period. Our current specification lacks the relevant wage data to control directly for changes in production worker and nonproduction worker wages, so we incorporate individual effects into our model in attempt to control for these within-firm changes. In later versions of the paper, we will be able to incorporate industry-specific and even firm-specific wage data, drawing up on Census firm-level records. In all cases we take natural logs of the variables and do not incorporate first differences as these differences should be captured in the individual effects.

6 The evolution has been complicated by employment "polarization," with American job creation in recent decades concentrated in high-skill intensive jobs and low-skill intensive jobs. A hollowing out of middle-skill, middle-income jobs has led to wage declines for workers in these categories – unable to compete for high-skill intensive jobs they have fallen down the skill ladder. See Autor and Dorn (2013) for a recent explanation.

Table 5: Impact of AI Innovations on Labor Demand, 1997-2016 (manufacturing firm only)

	Ln Production Worker Share
AI Treatment (1/0)	-0.00236
	(0.00884)
Ln Capital Stock	-0.000851*
	(0.000431)
Age	-0.0111***
	(0.000917)
Multinational Status (1/0)	0.000813
	(0.00114)
Firm Fixed Effects	Yes
Year Fixed Effects	Yes
Observations	1,614,000
R-squared	0.679

Robust Standard Errors clustered at the 4-digit NAICS industry level. *, ** and *** denotes significance at the 5%, 1% and 0.1% respectively. Each regression includes a constant, which is not displayed here.

Our results using this approach suggest that transition into AI invention has no impact on the firm's own production worker share. Given the across-firm differences in production worker share, these firms are likely already relying on fewer production workers and the advent of AI does not contribute to any substantial changes in this measure.

a.3 Earnings

Although within-firm changes in the share of production workers resulting from transition into AI invention appear to be negligible, there may changes in the earnings distributions of workers within these firms. Three decades of research in labor economics document the dispiriting reality that less educated Americans have faced relatively weak demand for their services, stagnant or declining wages, and an increasingly polarized job market (Autor, Katz, and Kearney, 2008; Autor and Dorn, 2013). While a number of other economic forces, including globalization, declining union density, and falling minimum wages, have also contributed to rising income inequality over the past four decades, economists generally agree that skill-biased technological change may be the single most important cause (Autor, 2014). If AI invention really does transform the economy to the degree that proponents expect, then it may significantly accelerate and exacerbate the kind of skill-biased technological change already documented by labor economists. We examine whether this is the case by linking our firms – both the AI-inventing firms and their same-industry peer firms – to the Longitudinal Employer Household Dynamics (LEHD) database widely used by labor economists. We are able to conduct this match for firms and establishments in 49 out of 50 states. In principle, this allows to probe the impact of transition into AI invention on the distribution of employee earnings within firms over time.

Our analysis on the changes to the earnings distribution follows the general methodology in Autor, Katz and Kearny (2008), who look at changes to the 90-10, 90-50 and 50-10 earnings ratios. We do something similar for our set of firms and estimate an equation along the lines of:

$$dER_i = \beta_0 + \beta_1 dln(L_i) + \beta_1 dln(K_i/Y_i) + \beta_2 dln(A_i) + \varepsilon_i$$

where ER reflects either the 90-10, 90-50 or 50-10 earnings ratios of firm i over some period of time, modeled as a function of changes in the employment L, capital intensity of firm i, (K_{it}/Y_{it}), and a measure of changes in the AI-intensity of firm innovation, A_{it}, over the same time period. We incorporate individual firm fixed effects into our model. In all cases we take natural logs of the key variables.

Table 6: Impact of AI Innovations on 90-10, 90-50 and 50-10 Earnings Ratio, 1997-2016 (manufacturing firm only)

	90-10 Earnings Ratio	90-50 Earnings Ratio	50-10 Earnings Ratio
AI Treatment (1/0)	0.0449***	0.0202	0.0230***
	(0.0131)	(0.0113)	(0.00562)
Ln Employment	-0.0873***	-0.0711***	-0.0154***
	(0.00127)	(0.00109)	(0.000542)
Ln Capital Stock	-0.00902***	-0.00859***	-0.000123
	(0.000739)	(0.000636)	(0.000317)
Age	-0.00370*	-0.00697***	0.00315***
	(0.00146)	(0.00125)	(0.000624)
Multinational Status (1/0)	0.00521**	0.00340*	0.00178*
	(0.00175)	(0.00151)	(0.000752)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	1,614,000	1,614,000	1,614,000
R-squared	0.743	0.740	0.666

Robust Standard Errors clustered at the 4-digit NAICS industry level. *, ** and *** denotes significance at the 5%, 1% and 0.1% respectively. Each regression includes a constant, which is not displayed here.

As Table 6 highlights, the within-firm effect of taking out an AI patent leads to a rise across all of the different earnings ratios, with the 90-10 and 50-10 ratios being significant. An AI patent is associated with a 4.5% change in the 90-10 earnings ratio and a 2.3% rise in the 50-10 ratio. There is also a rise in the 90-50 ratio, but it is not significant. This is suggestive that the adoption of AI technology is leading to further earnings inequality, but not necessarily polarization, as the median worker's income is also rising relative the lowest worker. However, the median worker's earnings are not rising as fast as the highest earning workers in the firm.

To summarize, our preliminary results using standard linear approaches to measuring the impact of AI show that innovating in AI is positively and significantly associated with higher revenue per employee, increased value added per worker and TFP, after controlling for firm fixed effects.

On the other hand, we do not see a within-firm change in the production worker share for firms who innovate in AI within the time horizon, but do see a rise in income for the 90th percentile and 50th percentile workers relative to the lower worker. This rise is highest among the 90th percentile workers, suggesting increased demand for the highest-skilled workers.

While this section attempts to control for these across-firm differences by limiting our analysis to within-firm changes, in the next section, we attempt to do a better job by performing an event study that pairs our AI-inventing firms with a comparable set of similar control firms.

b. Event Study

Our first pass of the data found positive and significant within-firm changes to revenue and value-added resulting from innovations in AI. This section attempts to better control for some of the endogeneity described earlier, as well as look at firm behavior and outcomes before and after the AI innovation. We do this by conducting an event study analysis (e.g. a difference-in-differences specification with a group-specific time trend) centered around the timing the first AI-related patent. Our identification relies on matching each firm with at least one AI-related patent as closely as possible with a similar same-industry counterpart which does not obtain an AI-related patent. We can accomplish this using the full richness of the Census data.

b.1 Exact Matching of Firms with AI patents

Our event study begins by attempting to identify an exact match of the firm with an AI-related patent. Our matching criteria are based on firm age, firm industry, multi-unit status, and firm size and are centered around the timing of the first AI patent application (e.g. if a firm took out its first AI patent in 2001, we would attempt to identify a matching non-AI patenting firm in 2001) . We group the AI firms into 12 age bins[7], a 4-digit NAICS industry (based on the largest employment firm-4-digit NAICS employment), multi-unit status (1 if multi-unit, 0 if otherwise) and 50 different size bins (based on employment).[8] We then match the AI firms with their exact counterpart in the year of the AI application. We are able to identify exact matches for 96% of the firms with an AI patent. AI firms with multiple *n* matches are assigned a weight that is the inverse of the number of matched firms (*1/n*).

b.2 Event Study Plots

Before looking at the regression results, it will help to look at the event study plots centered around the time of the first AI innovation. Our figures below are centered 2 years prior to the first AI innovation and track firm performance in the 5 years following the AI innovation. We start with employment. Figure 7 looks at the relative employment growth in the pre and post AI

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[7] Each bin is Year 0, Year 1, Year 2, Year 3, Year 4, Year 5, Year 6-7, Year 8-9, Year 10-12, Year 13-15, Year 15-20 and Year 20+

[8] We attempted to first match by 6-digit NAICS industry, but our match rate was not high enough (~80%). We have also experimented with different size bins, including both more bins and fewer bins. Neither of these specification changes significantly affects our analyses.

patent application date for the AI firms and their matched counterpart. We set our relative employment to 1 at the time of the AI patent application.

Our exact match of the firm types should show that the pre-period trends follow relatively closely, which is confirmed in the plot depicted in Figure 7. In the years following the AI patent application however, employment growth for AI patenting firms deviates relative to the employment growth of non-AI patenting firms. In fact, we find that employment growth is 25% higher in the five years following the first AI patent application.

We construct a similar event study plot, charting the revenue for AI patenting firms and non-AI patenting firms. Figure 8 shows the results. We see similar patterns as in Figure 7, with the pre-period trends following closely for the two firm types and then deviating in the years following the first AI application. In the 5 years following the first AI patent application, AI firms have 40% higher revenue than their counterparts.

b.2 Event Study Specification

We now move to a more formal specification that includes firm controls and assesses whether the deviation in employment and revenue growth persists after controls are introduced. Our event study looks at the difference-in-differences of the firm outcomes and includes a group specific time trend. Our specification is as follows:

$$y_{it} = \alpha + \beta_1 AI_{it}(1|0) + \beta_2 POST + \beta_3 AI_{it} \times POST + X_{it} + \varepsilon$$

with firm controls for earnings, age, multi-unit status and multinational status. The β_1 coefficient indicates the aggregate effects of having an AI patent on the outcome variable, while β_2 measures aggregate time trends. The β_3 coefficient indicates whether the impact of AI patents is changing over time on the outcome variable.

In our empirical analyses, we split our sample between the full matched dataset and a manufacturing-only dataset with different outcome variables for each. The full matched dataset will include employment and revenue per employee as the primary outcome variables, while the manufacturing-only sample will examine value-added per employee and production worker share.[9] Table 7 provides the first set of results.

[9] Value-added and production worker are not available for the full sample.

Table 7: Impact of AI Innovations on Employment and Revenue, 1997-2016 (full matched set of firms)

	Ln Employment	Ln Revenue per Employee
AI Treatment (1/0)	0.0810***	0.0415***
	(0.00220)	(0.00365)
Post AI Year	-0.0816***	-0.0495***
	(0.00210)	(0.00357)
AI Treatment x Post AI Year	**0.133*** **	**0.0680*** **
	(0.00251)	**(0.00434)**
Age	0.275***	0.264***
	(0.00186)	(0.00384)
Multinational Status (1/0)	0.143***	0.0158***
	(0.00265)	(0.00463)
Industry Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	1,692,000	1,692,000
R-squared	0.982	0.803

Robust Standard Errors clustered at the 4-digit NAICS industry level. *, ** and *** denotes significance at the 5%, 1% and 0.1% respectively. Each regression includes a constant, which is not displayed here.

After controlling for other firm characteristics, we find that the impact of AI patents is positive on both employment and revenue per employee; having an AI patent is associated with 8.1% higher employment and 4.15% higher revenue per employee, with the impact for each growing over time. For treated firms, each additional year is associated with a 13.3% increase in employment and a 6.8% increase in revenue per employee.

These effects are expected to differ across different sectors of the economy, whose implementation of AI are likely to differ, and therefore have differential effects on either employment or revenue. To ascertain these effects, we focus on revenue per employee and subset our baseline set across 9 different sectors. We focus exclusively on the post-treatment effect (defined as the AI Treatment x Relative AI Year). The coefficient plot for the sectoral breakdown can be found in Figure 9a. For most industries, the post-treatment effect of AI patents has a positive impact on revenue per employee. The two sectors where this is not the case are manufacturing the finance (includes finance, insurance and real estate).

In Figure 9b, we further decompose the manufacturing sector by 3-digit NAICS, and find that the cumulative negative impact of the post-treatment effect stems primarily from the Chemicals (NAICS 324 and 325) and Other (NAICS 312-316 (Food, Beverage and Textiles), 337 (Furniture) and 339 (Miscellaneous)). In Figure 9c, we subset the Professional Services sector by 4-digit NAICS and find that the positive cumulative post-treatment effect for professional services is primarily a result of the positive impact of AI patents in Specialized Design (NAICS 5414 and 5415) and Other (NAICS 5411-12 (Legal and Accounting), NAICS 5418-19 (Advertising and Other)).

b.3 Earnings Ratios (Event Study)

We perform a similar estimation as in Table 6 looking at the earnings ratio for the matched set of firms. To frame our analysis, we start by comparing the earnings ratios for our matched sample with those documented in Hyatt and Spletzer (2017), who take a 20-state balanced panel over a similar time period. This comparison can be found in Figure 10. While the 90-10 ratios are almost identical, the 90-50 ratios between the 20-state sample in Hyatt and Spletzer (2017) and our matched propensity score sample diverge, with the matched sample staying mostly flat, whereas the Hyatt-Spletzer sample showing the wage polarization documented in Autor, Katz and Kearney (2008). This is likely due to the sector-level differences in the matched AI sample, as well as firm-differences (the matched sample tends to be larger, higher average payroll per worker, etc…). Finally, the 50-10 ratios follow a similar pattern, with the magnitude of the rise being smaller in the AI-matched sample. This first comparison suggests that we should see a rise in the 90^{th} and 50^{th} percentile earnings for our sample.

We next plot the change in the earnings ratio centered around the time of the first AI patent, as in the previous event study plots in Figures 7 and 8. This can be found in Figure 11. As Figure 11 shows, we see some divergence in the 90-10 earnings ratio between the AI set of firms and the control set, with little divergence in the 90-50 and 50-10 earnings ratio.

We next control for other firm characteristics and estimate the potential impact of the treatment, as in Tables 6 and 7. Our main results focus on the across-firm effects. Table 8 provides the set of results.

Table 8: Impact of AI Innovations on 90-10, 90-50 and 50-10 Earnings Ratio, 1997-2016 (full matched set of firms)

	90-10 Earnings Ratio	90-50 Earnings Ratio	50-10 Earnings Ratio
AI Treatment (1/0)	-0.0377***	-0.00690**	-0.0213***
	(0.00324)	(0.00220)	(0.00210)
Post AI Year	-0.00375	-0.00162	-0.00477**
	(0.00275)	(0.00186)	(0.00178)
AI Treatment x Post AI Year	**0.0108****	**0.00321**	**0.0142*****
	(0.00349)	**(0.00237)**	**(0.00226)**
Ln Employment	0.0537***	0.0204***	0.0410***
	(0.00171)	(0.00115)	(0.00111)
Age	-0.0690***	-0.0561***	-0.00927***
	(0.00282)	(0.00190)	(0.00182)
Multinational Status (1/0)	-0.00884*	-0.00876***	-0.00538*
	(0.00367)	(0.00252)	(0.00239)
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	704,000	704,000	704,000
R-squared	0.712	0.704	0.682

Robust Standard Errors clustered at the 4-digit NAICS industry level. *, ** and *** denotes significance at the 5%, 1% and 0.1% respectively. Each regression includes a constant, which is not displayed here.

The post-treatment effect shows a positive and significant rise on all of the earnings ratio, with the 90-10 earnings ratio increasing by 1.1%, the 90-50 by 0.3% and the 50-10 by 1.4%. This continues to support the idea that the advent of AI is associated with a rise in earning inequality, as the earnings ratio increases the largest for the 90th percentile worker within each firm, followed by the 50th percentile.

b.4 Sales, Productivity and Labor Demand (Event Study)

We follow this analysis by examining a separate set of outcomes for only the manufacturing firms. Here our outcome variables are similar to the ones in Table 4 and Table 5 (sales per employee, value-added per employee, total factor productivity and production worker share). We incorporate the same controls as before, but include a post-year coefficient (1/0), rather than a relative-year, in order to capture the within-firm effects.

Table 9: Impact of AI Innovations on Sales, Productivity and Workforce Composition, 1997-2016 (matched set of manufacturing firms)

	Ln Total Value of Shipments Per Employee	Ln Value-Added per Employee	Ln Total Factor Productivity (TFP)	Ln Production Worker Share
AI Treatment (1/0)	-0.00516	0.0153	0.0121	-0.0313*
	(0.0217)	(0.0263)	(0.0178)	(0.0149)
Post AI-Year (1/0)	0.0349	0.0601*	-0.0452*	0.00401
	(0.0251)	(0.0305)	(0.0220)	(0.0172)
AI Treatment x Post-Year	**-0.0274**	**-0.0700***	**0.0256**	**-0.0103**
	(0.0290)	**(0.0352)**	**(0.0244)**	**(0.0199)**
Ln Capital Stock	0.137***	0.114***	-0.0541***	-0.0159*
	(0.0113)	(0.0137)	(0.0103)	(0.00778)
Age	-0.0539	0.00389	0.0281	-0.0201
	(0.0356)	(0.0433)	(0.0396)	(0.0244)
Multinational Status (1/0)	-0.144***	-0.162**	-0.0246	-0.0194
	(0.0429)	(0.0520)	(0.0379)	(0.0295)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	8,900	8,900	8,900	8,900
R-squared	0.958	0.942	0.808	0.788

Robust Standard Errors clustered at the 4-digit NAICS industry level. *, ** and *** denotes significance at the 5%, 1% and 0.1% respectively.

We see that the within-firm impact for the propensity-matched manufacturing firms of AI patents mostly negligible. While AI treated firms have a lower production worker share than non-AI treated firms, the post-treatment effect is not significant. For the other variables, we also see little to no change in the post-treatment outcomes of total value shipments and TFP, with value-added per employee declining marginally.

To conclude, the event-study propensity-score matched firm identified a number of interesting associations between AI usage and firm outcomes. While the propensity-score matched firms do a reasonable job of identifying a set of control firms, there are still flaws with this approach as we were unable to include innovation characteristics in generating our matches. Likewise, our event-study specification is intended to identify treatment impacts that may occur several years after the initial treatment, but we neglect to include an intensity measure for the treated, and have a limited post-period to look at due to the recentness of the patent data. Therefore, while these statistical associations are suggestive, it would be premature to view them as providing strong evidence of a *causal* relationship between AI innovation and the measured outcomes. It may be the case that as the firm invests in AI innovations, other structural changes are taking place within the firm, such as automation, new capital expenditures and more. Coming to strong conclusions about causality will require additional data and further analyses.

To conclude our analysis, we perform several separate specifications that identify similar impacts of AI innovations on firm outcomes and behavior. In the more traditional approach, we find that the within-firm effects of AI patents are associated with higher revenues, productivity and earning inequality. We do not find within-firm effects on the production worker share, but demonstrate that firms with AI patents tend to begin with significantly fewer production workers.

We attempt to better control for the endogeneity in the decisions that would lead to greater investing in AI related innovations, by performing an event study using a matched set of firms based on age, size and industry at the time of the first AI patent. Our results continue to hold where the set of AI firms show a positive and significant deviation in employment and revenue from the matched comparable set of firms, along with rising earning inequality. However, many of the productivity changes captured in the within-firm analysis do not hold in the event-study analysis.

VII. Conclusions

Significant breakthroughs in AI and related technologies have led some economists to predict dramatic effects on firm productivity and labor demand. However, empirical assessment of the actual impact has been limited by a lack of good firm-level data on AI innovation and its economic effects. In the absence of data on firm behavior, much recent scholarship has been prospective or predictive in nature, using information on the task content of jobs to assess which occupations might change as a consequence of rising AI capabilities.

While this is useful, it is not the same as observing the ways that labor demand and productivity of actual firms are changing as they increase their investment in AI technologies. This paper advances our understanding of the economic impact of AI by using patent data to capture AI-related innovation in a new way. Previous analyses by economists have sought to measure AI-related innovation by focusing on a small number of keywords and patent classes. Instead, we use a suite of machine learning algorithms to parse the entire text of patent documents; our more comprehensive search yields a much larger count of AI-related patents than have been identified in earlier studies. The sharp rise in patenting and its wide distribution across patent classes and firms are consistent with the characterization in the literature of AI as a general purpose technology.

Because we know the identity of patent assignees, we can match the patent data to extensive confidential microdata on these firms collected by the U.S. Census Bureau. These rich data are available for publicly traded and privately held firms, and they allow us to take a first look at the impact of AI innovation on the productivity and labor demand of the innovating firms. The results of such analyses may be useful for researchers and policymakers, because the impact observed in the limited number of leading firms in this space could be indicative of the larger impact we will see as this technology spreads across firms and industries. Such analyses also provide a useful counterpoint to recent scholarship that seeks to predict labor market impacts based on textual analysis of occupations, tasks, and emerging AI capabilities.

We have begun to expand our analyses of the impact of growing AI invention on labor demand by matching our firm-level data to the Longitudinal Employer-Household Dynamics (LEHD) data set. This enables us to quantify the impact of AI innovation on the entire wage distribution of AI-inventing firms. We find that the inception of AI invention is associated with statistically and economically significant increases in within-firm wage inequality. The richness of the Census data enables us to trace out differences in this impact across time and industries. Given the importance of the topic, deeper investigation with these rich data may yield useful insights for researchers and policymakers.

Our current explorations are preliminary, and it would be premature to interpret our statistical results as strong evidence of causal impacts. Nevertheless, our results suggest that the inception of AI innovation is associated with economically and statistically significant increases in revenue and value-added per employee, suggesting strong productivity effects, and increases in within-firm wage inequality. Not surprisingly, AI-inventing firms tend to be large, R&D-performing enterprises that register large numbers of patents. Efforts to refine our estimates of the impact of AI led us to conduct event-study style analyses on matched samples of AI firms and similar firms in the same industries that did not transition into AI patenting over our sample period. Our regression results on this matched sample continue to suggest quite large productivity effects and wage dispersion effects. that strengthen significantly over time. Despite the limitations of our current analyses, preliminary results suggest that this is promising line of research, which we will continue to explore.

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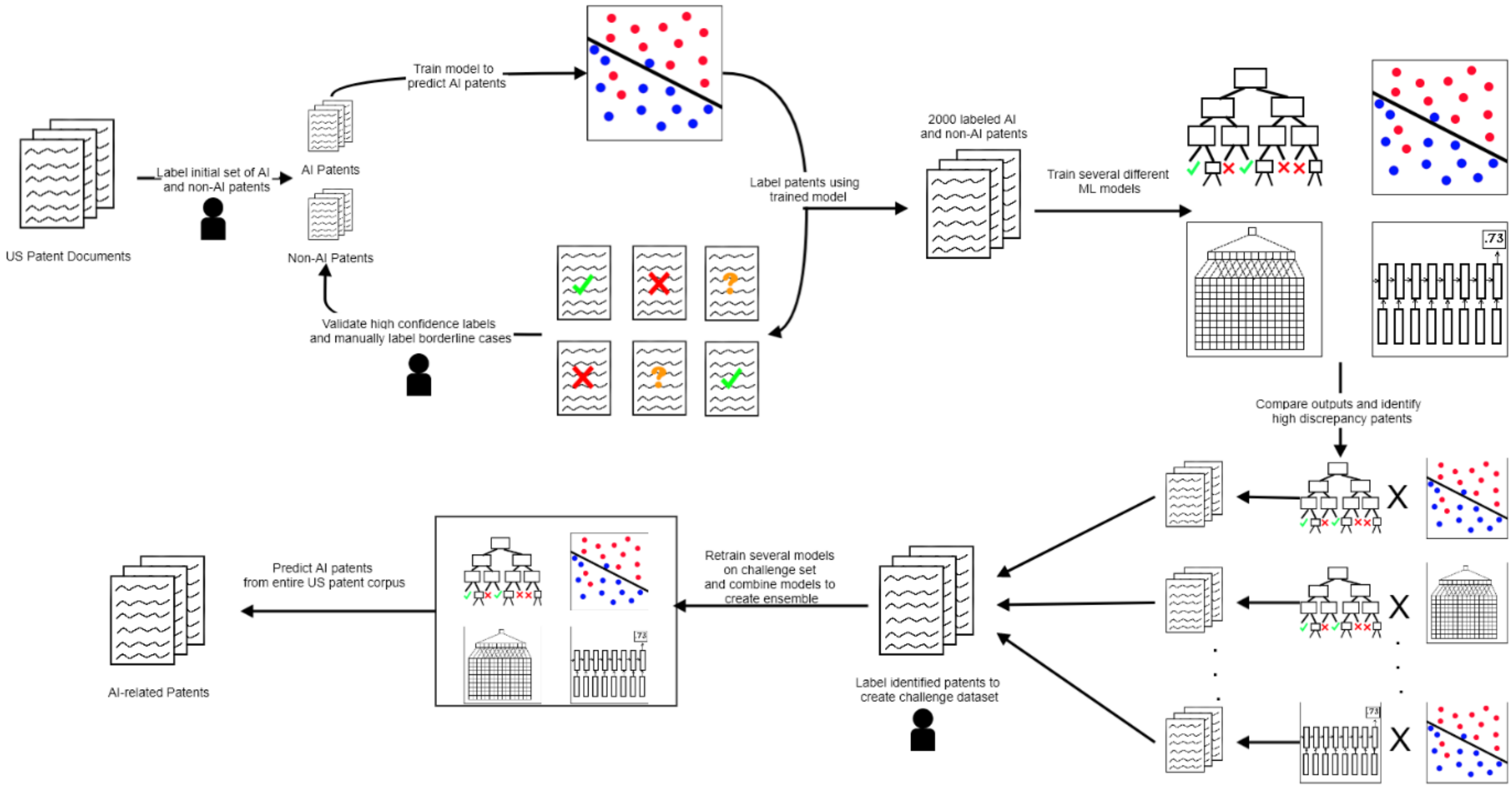


Figure 1. AI Patent Identification Algorithm

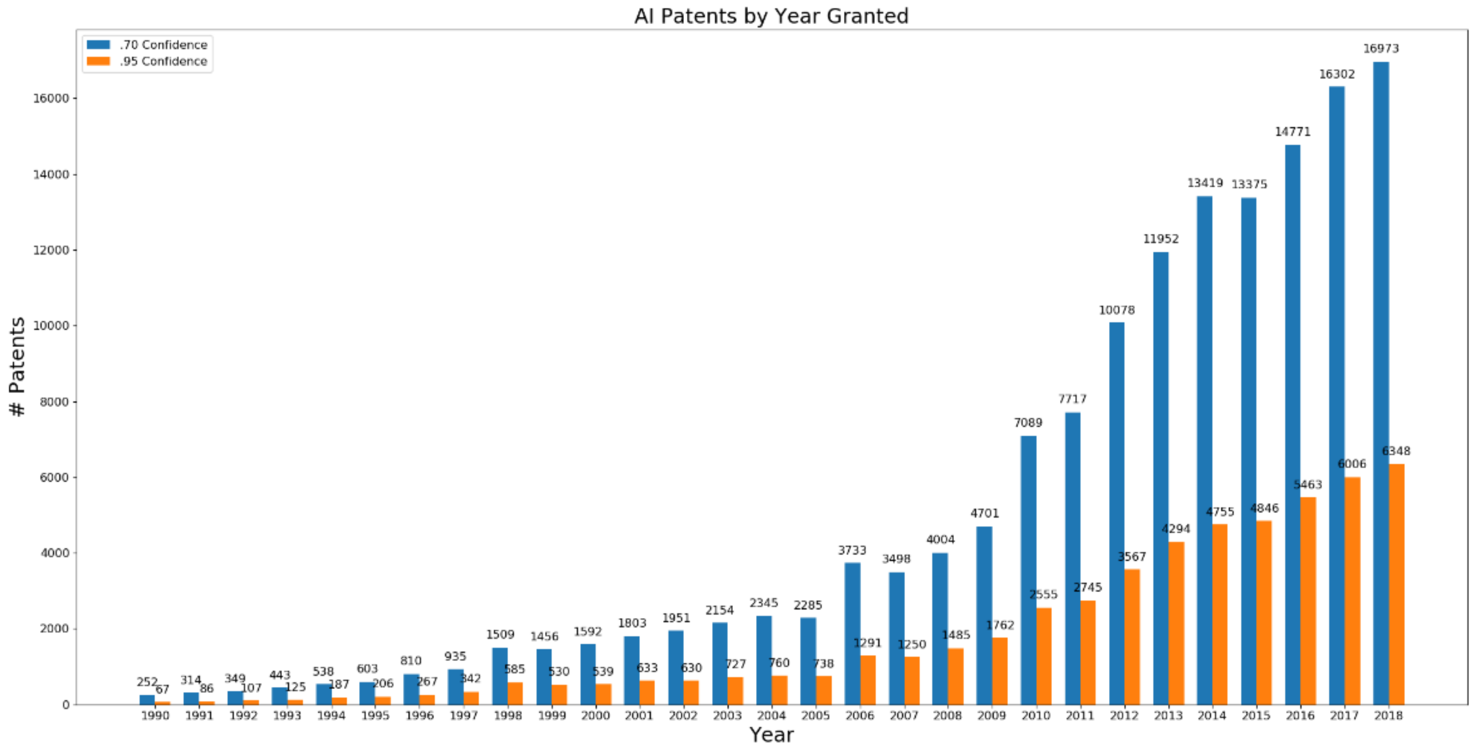


Figure 2. AI Patents by Grant Year

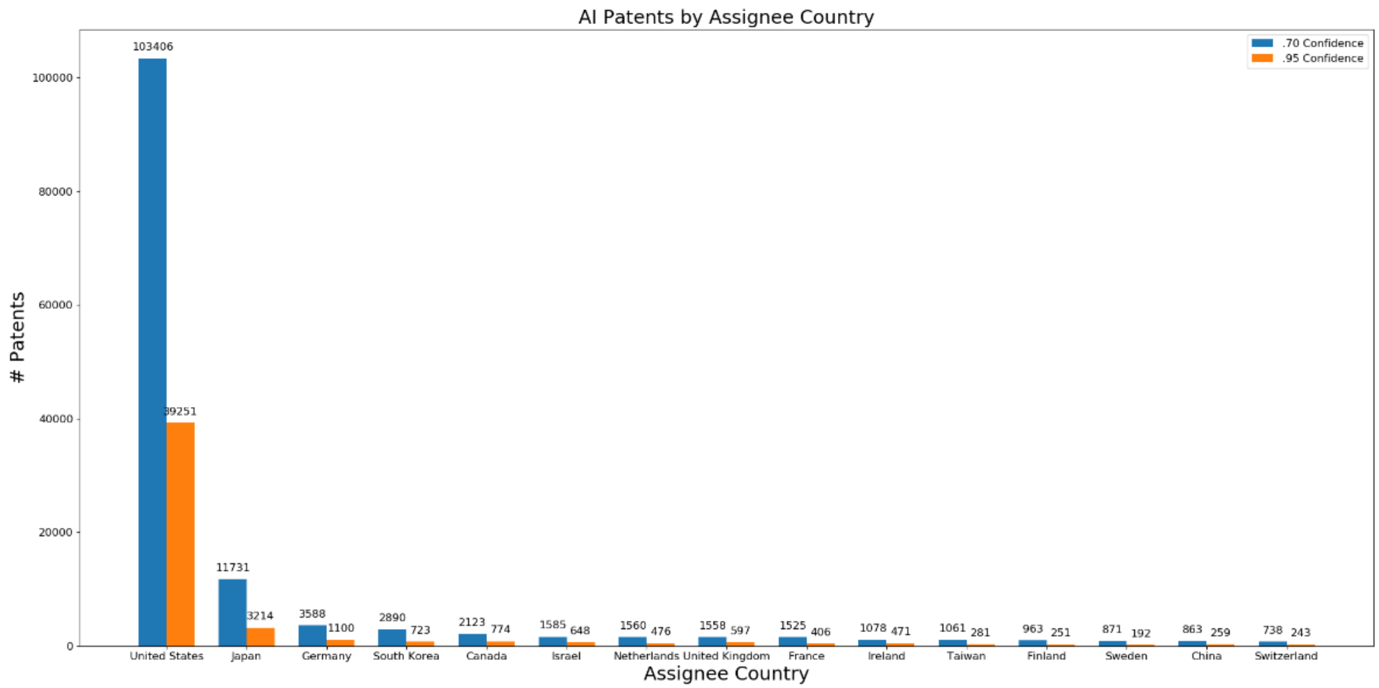


Figure 3. AI Patents by Country

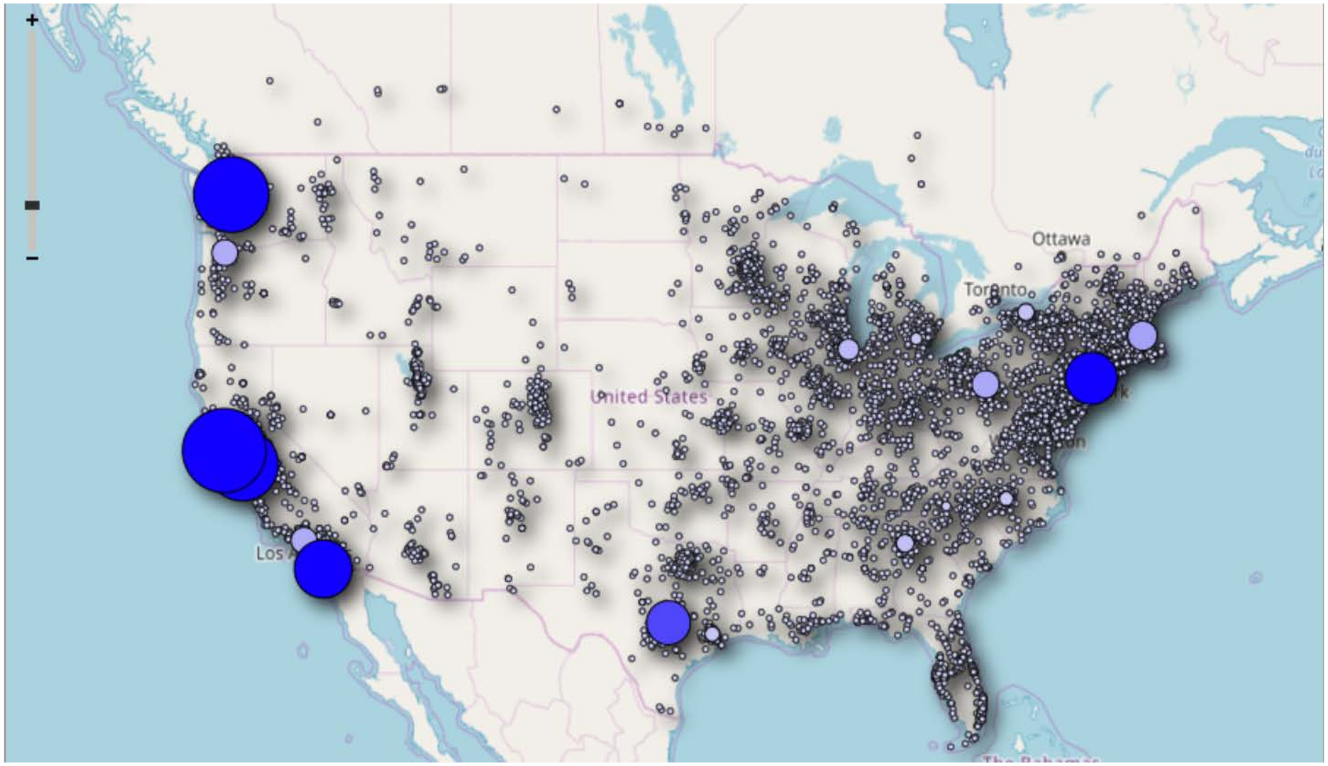


Figure 4 Inventor Heat Map of AI Patents in U.S

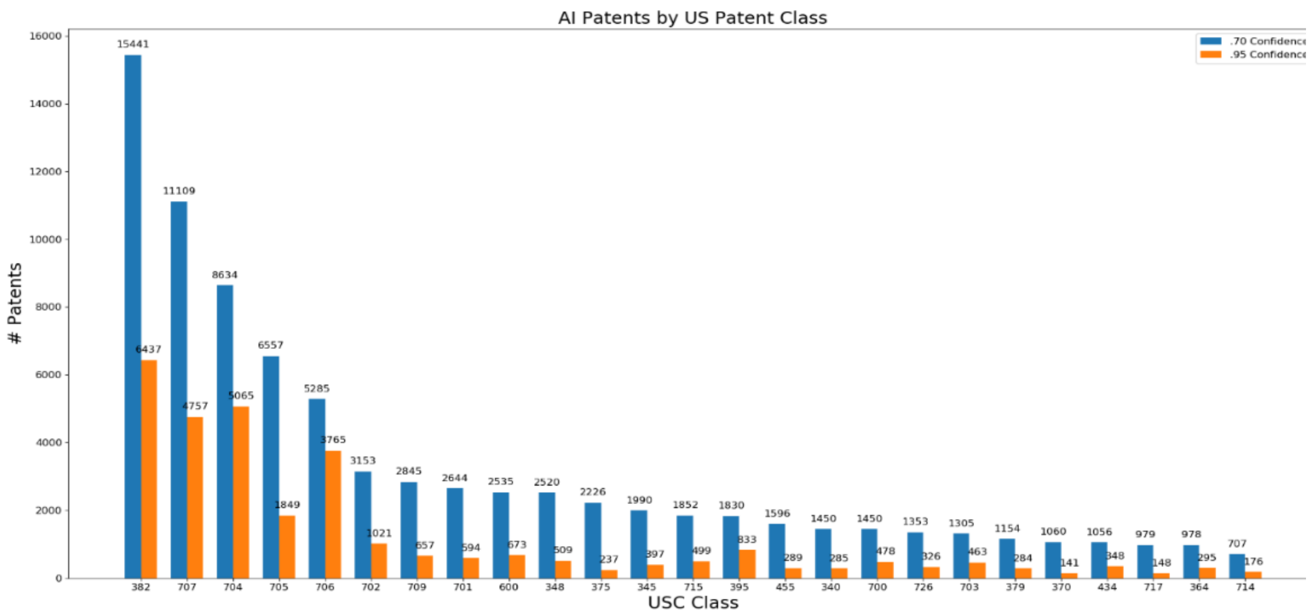
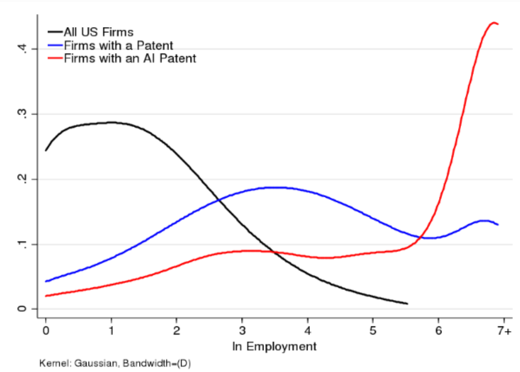
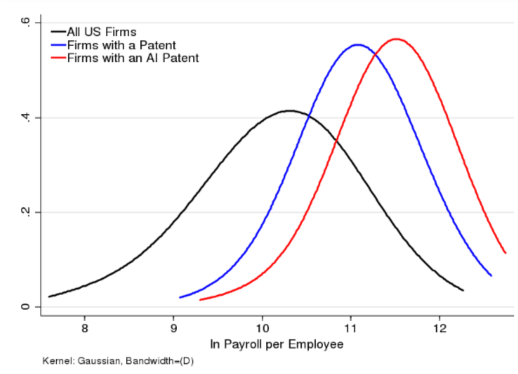


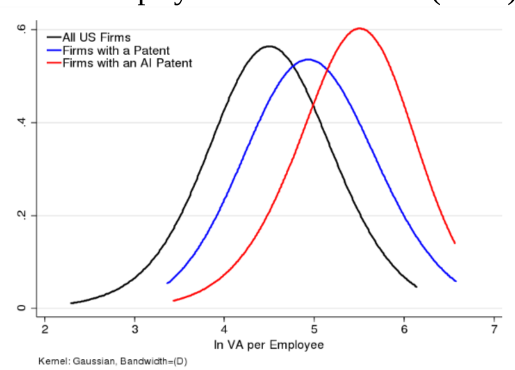
Figure 5. AI Patents by USPC Class



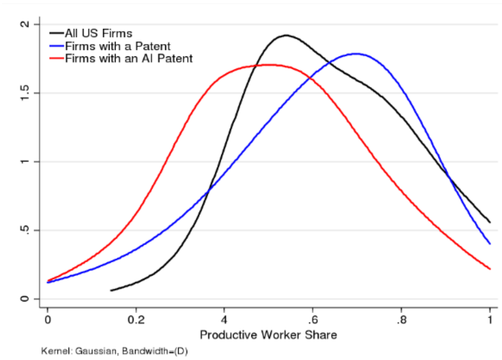
a. Employment Distribution (KDE)



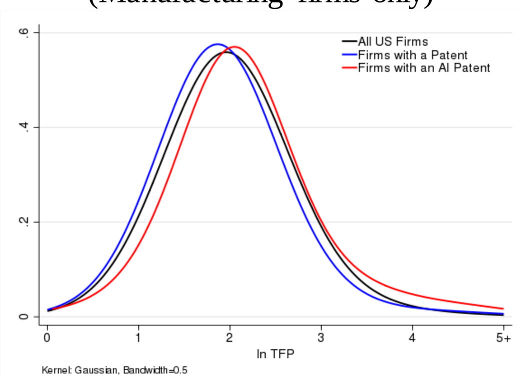
b. Payroll per Employee (KDE)



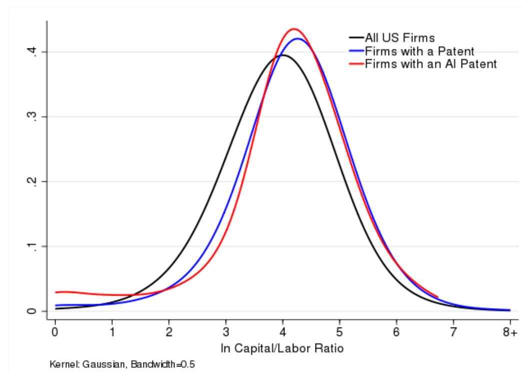
c. Value-Added per Employee (KDE) (Manufacturing firms only)



d. Production Worker Share (KDE) (Manufacturing firms only)



e. Total Factor Productivity (KDE) (Manufacturing firms only)



f. Capital/Labor Ratio (KDE) (Manufacturing firms only)

Figure 6. Kernel Density Plots of Firm Characteristics by Firm Type,

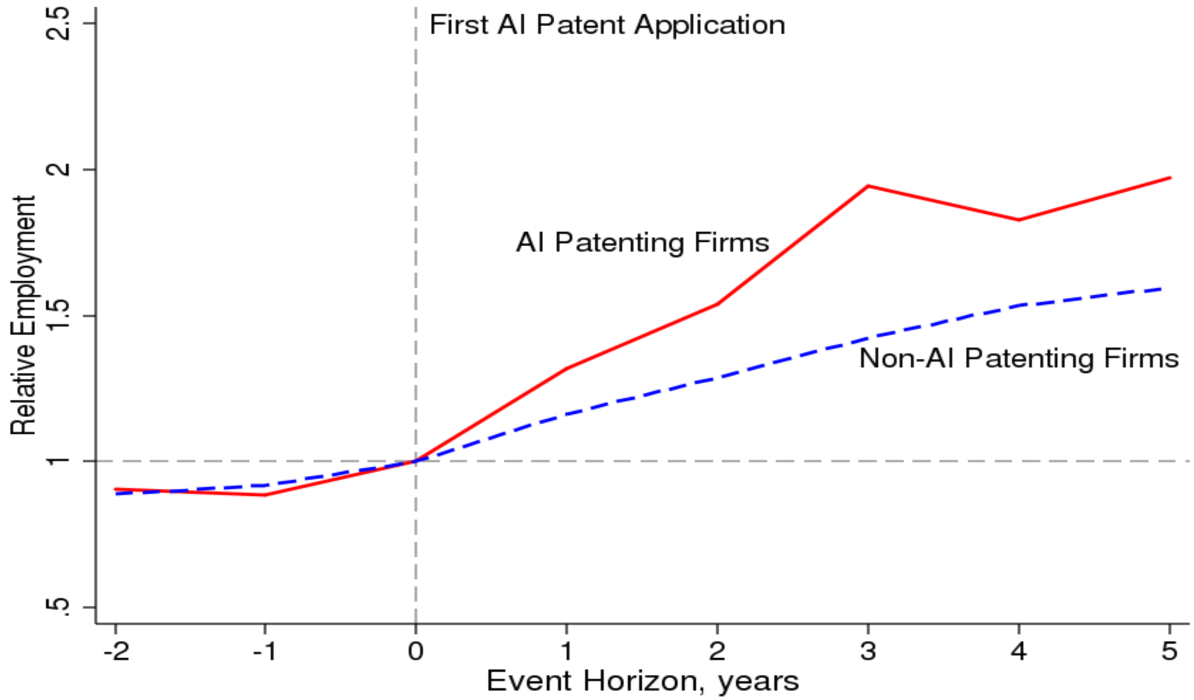


Figure 7. Pre/Post AI Patent Employment Growth

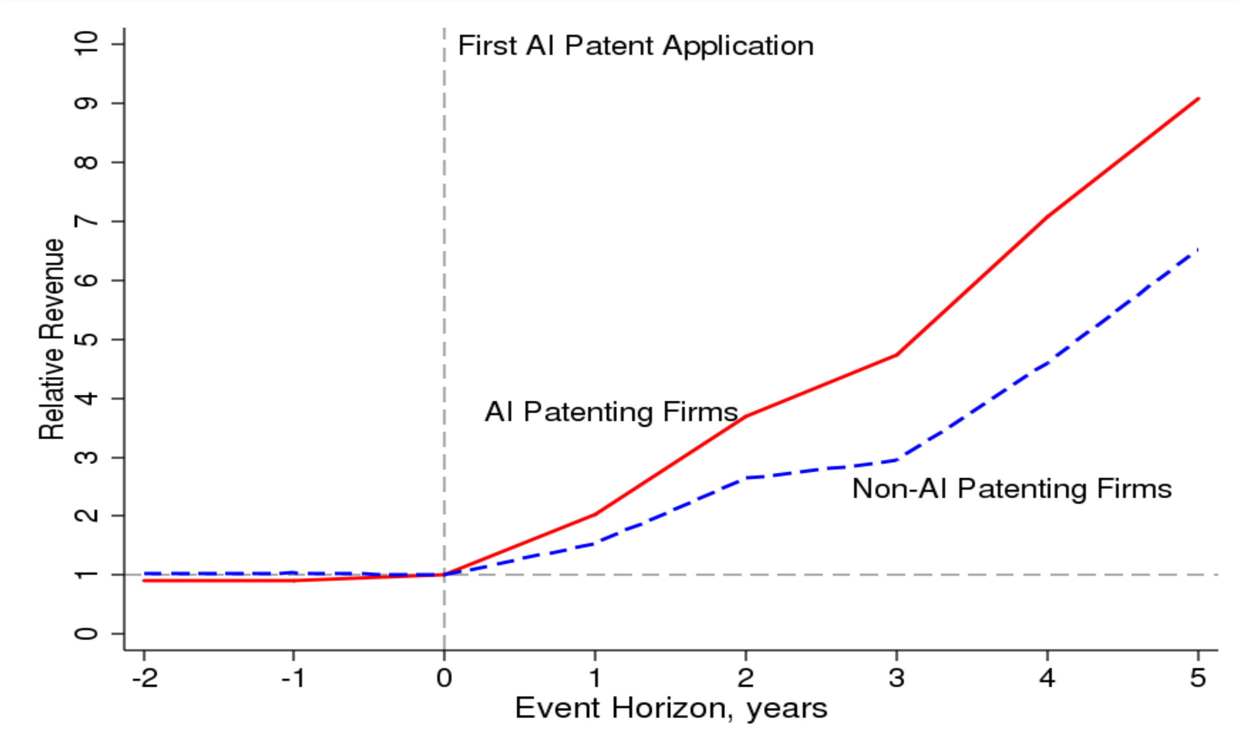
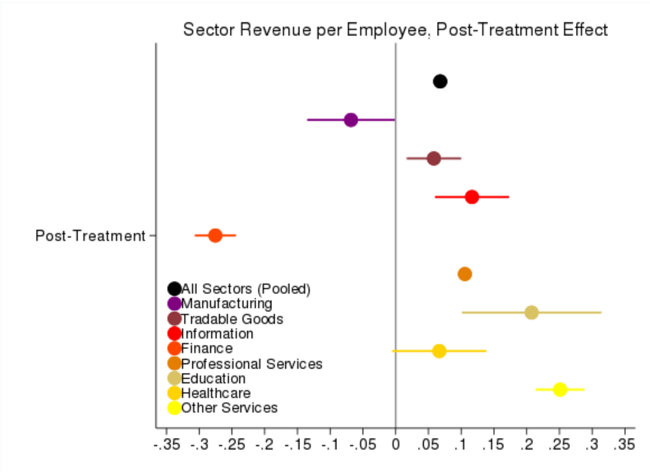
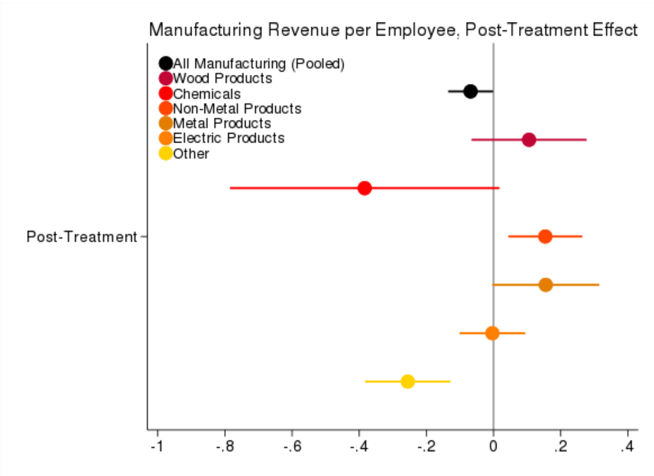


Figure 8. Pre/Post AI Patent Revenue Growth



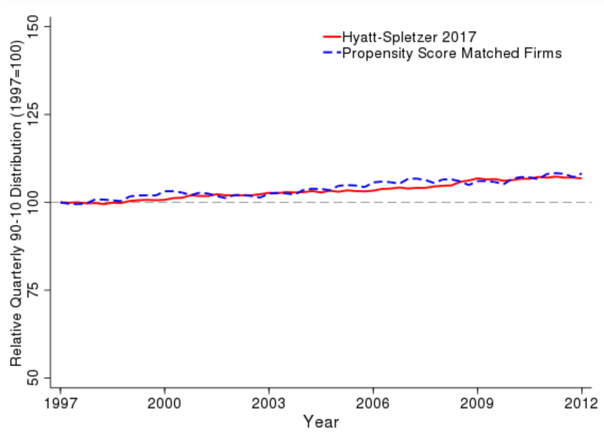
a. By 2-digit NAICS Sector



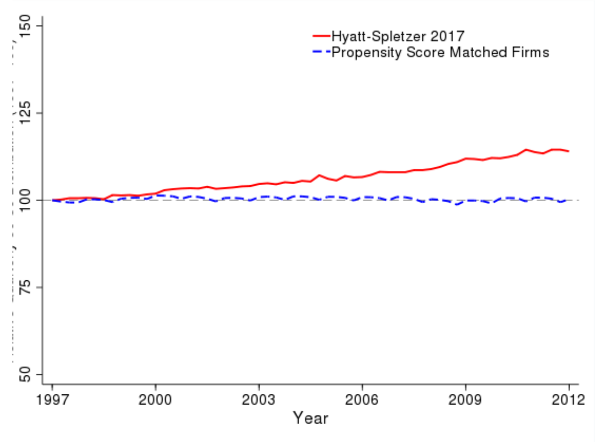
b. By 3-digit NAICS Sector (Manufacturing)

c. By 4-digit NAICS Sector (Professional Services)

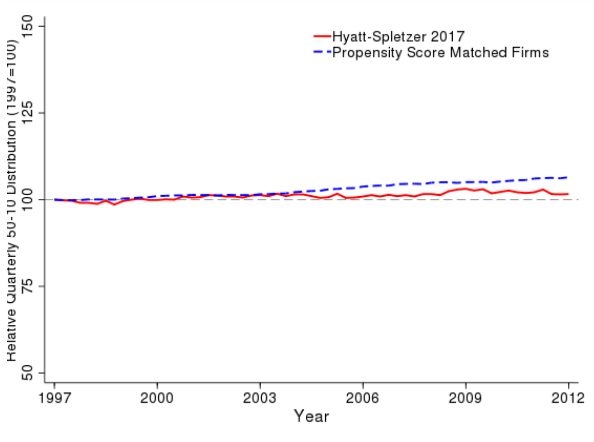
Figure 9. Sectoral Comparison of AI Treatment x Post



a. 90-10 Earnings Ratio

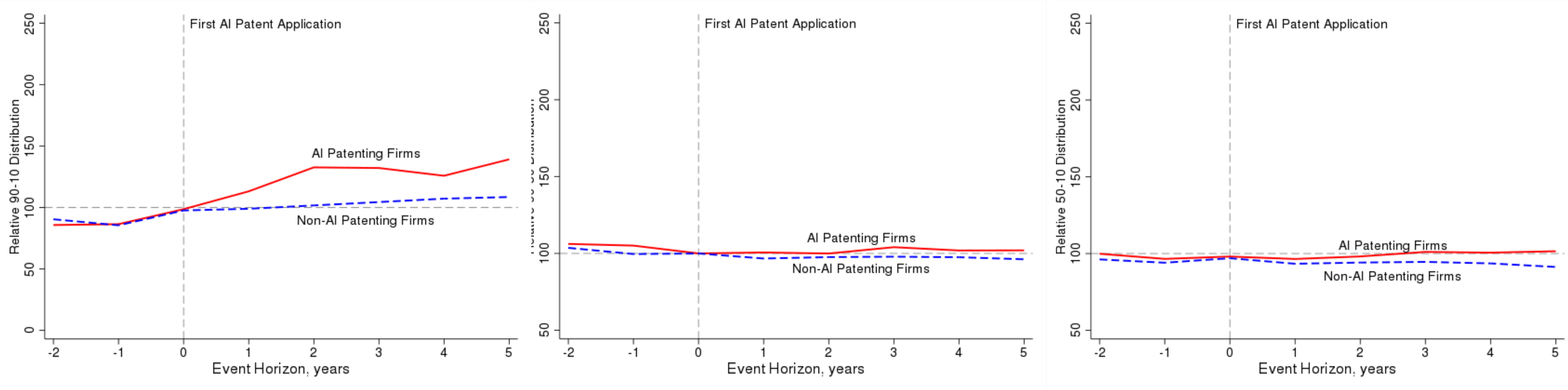


b. 90-50 Earnings Ratio



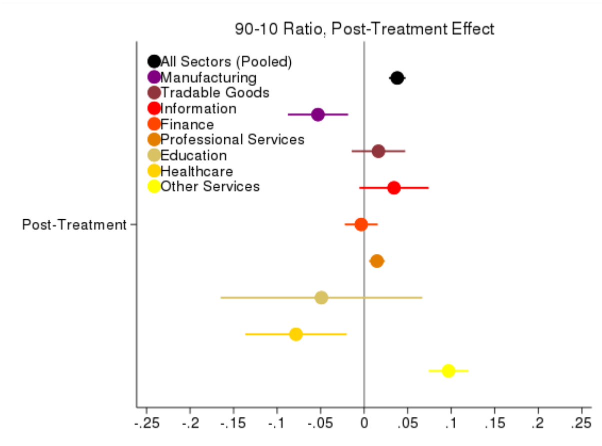
c. 50-10 Earnings Ratio

Figure 10. Earnings Ratio Comparison with Hyatt-Spletzer (2017)

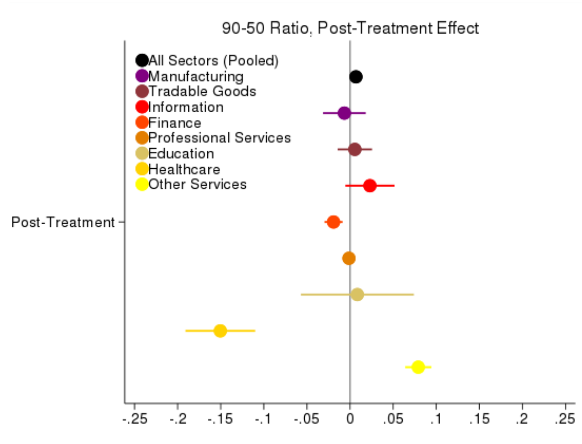


d. 90-10 Earnings Ratio   e. 90-50 Earnings Ratio   f. 50-10 Earnings Ratio

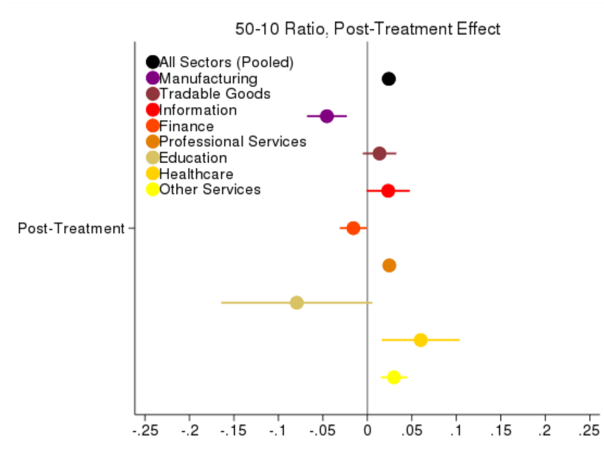
Figure 11. Pre/Post AI Changes to Earnings Ratio



a. 90-10 Earnings Ratio



b. 90-50 Earnings Ratio



c. 50-10 Earnings Ratio

Figure 12. Sectoral Decomposition of AI Post-Treatment effect on Earnings Ratios