The Impact of Artificial Intelligence on the Labor Market

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Abstract

I develop a new method to predict the impacts of any technology on occupations. I use the overlap between the text of job task descriptions and the text of patents to construct a measure of the exposure of tasks to automation. I first apply the method to historical cases such as software and industrial robots. I establish that occupations I measure as highly exposed to previous automation technologies saw declines in employment and wages over the relevant periods. I use the fitted parameters from the case studies to predict the impacts of artificial intelligence. I find that, in contrast to software and robots, AI is directed at high-skilled tasks. Under the assumption that historical patterns of long-run substitution will continue, I estimate that AI will reduce 90:10 wage inequality, but will not affect the top 1%.

Keywords: artificial intelligence, robotics, technology, patents, occupations

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New technologies create winners and losers in the labor market. They change relative demands for occupations, even as they improve productivity and standards of living.[1] Understanding these distributional consequences is important for many purposes. For example, it allows policymakers to design appropriate education and skills policies, and helps individuals make good choices about what careers to pursue.

Today, one technology is causing particular anxiety about job displacement: artificial intelligence. Artificial intelligence, or machine learning, refers to algorithms that learn to complete tasks by identifying statistical patterns in data, rather than following instructions provided by humans. This technology has recently achieved superhuman performance across a wide range of economically valuable tasks. Some of these tasks are associated with high-wage occupations, such as radiologists, while others are associated with low-wage occupations, such as agricultural workers. At a time when rising inequality is a major social and political issue, it is unclear whether AI will increase inequality by, say, further displacing production workers, or reduce it by displacing doctors and lawyers.

In this paper, I develop a new method for identifying which tasks can be automated by any particular technology. This allows me to construct a measure of the "exposure" of occupations to that technology. I first apply the measure to two historical case studies, software and robots. I document the tasks that patents describe these technologies as performing, characterize the kinds of people who work in exposed occupations, and study the relationship between my exposure scores and changes in employment and wages. I then apply the method to artificial intelligence. I show that AI exposure is highest for high-skilled occupations, suggesting that AI will affect very different people than software and robots. Finally, I impose the assumption that the historical relationship between exposure scores and wage changes will persist, and use this relationship to estimate the potential impacts of artificial intelligence on inequality.

The measure developed in this paper is based on the following key idea. The text of patents contains information about what technologies do, and the text of job descriptions contains information about the tasks people do in their jobs. These two text corpuses can be combined to quantify how much patenting in a particular technology has been directed at the tasks of any particular occupation. This is therefore a measure of the tasks from which labor may be "displaced", in the canonical task-based model of Acemoglu and Restrepo (2018).

I use verb-noun pairs to quantify the "overlap" between patents and tasks. Suppose a doctor's job description includes the task "diagnose patient's condition". I use a natural language processing

[1] For example, a large literature, starting with Autor, Levy, and Murnane (2003), has documented how software reduced demand for workers performing routine tasks while increasing it for workers performing problem-solving and complex interpersonal tasks.

algorithm to extract the verb-noun pairs from this task, which in this case would be "diagnose condition". I then quantify how many patents corresponding to a given technology contain similar verb-noun pairs, such as "diagnose disease". I use the prevalence of such patents to assign a score to the task, and aggregate these task-level scores to the occupation level.

What can we learn from a measure of the tasks for which technology can substitute for human labor? As a framework for applying the measure, I develop a version of the Acemoglu and Restrepo (2018) task-based model, in which automation occurs at the task level. I add occupations to the model, so that occupations produce output using tasks, and firms produce output using occupations. The model shows that the impact of task-level automation on occupation demand is ambiguous. The intuition is simple. If half of an occupation's tasks are automated, that will reduce labor demand per unit of the occupation's output. But it might reduce the price of the occupation's output so much that demand for it increases enough to offset the reduction in labor demand, perhaps even producing a net increase in labor demand for the occupation. Similar opposing forces operate at other levels of the model. This means that without strong restrictions on the values of the various elasticity of substitution parameters, it is impossible to sign the net impacts of task-level substitution on the demand for occupations.

To study the performance of my measure empirically, and so help resolve this theoretical ambiguity, I analyze two historical episodes, software and robots. I chose these episodes because they affected many occupations in many industries. This breadth of impact is important because I use occupation-industries cells as the unit of analysis in my regressions. Moreover, because these technologies are so recent, they are more likely to be informative about how the economy will respond to artificial intelligence.

For each technology, I first document the tasks the patents describe it as performing. Patents most frequently describe robots as cleaning, moving, welding, and assembling various objects. By contrast, they describe software as recording, storing, and producing information, and executing programs, logic, and rules. When I aggregate from the task to the occupation level, I find that occupations most exposed to robots include various kinds of materials movers in factories and warehouses, and tenders of factory equipment, both of which have seen automation by robots. Least-exposed occupations include payroll clerks, artistic performers, and clergy. These do not primarily involve the kinds of repetitive manual tasks that robots automate. Occupations most exposed to software include broadcast equipment operators, plant operators, and parking lot attendants, all of which have seen computers take over large parts of their tasks. Least-exposed occupations include barbers, podiatrists, and postal service mail carriers. These are occupations that have substantial manual components that are not easy to hard-code in advance, and, in many cases, interpersonal components too.

Next, I study the kinds of individuals who work in occupations that are highly exposed to each technology. I find that individuals with less than high school education, and in low-wage occupations, are most exposed to robots. Men under age 30 are most exposed, consistent with robots' substituting for what might be termed "muscle" tasks. For software, exposure is decreasing with education, but much less sharply than for robots, with individuals in middle-wage occupations most exposed. This is consistent with the literature on polarization, which has found that I.T. has reduced demand for middle-wage jobs while increasing it for low- and high-wage jobs. Just as for robots, men are much more exposed to software than women. This reflects the fact that women have historically clustered more in occupations requiring complex interpersonal interaction tasks, which software is not capable of performing.

I conclude the case studies by estimating the relationship between my measure of occupation exposure and changes in employment and wages over the period 1980 to 2010. Although I cannot attribute causality to the exposure scores, moving from the 25th to the 75th percentile of exposure to robots is associated with a decline in within-industry employment shares of between 9 and 18%, and a decline in wages of between 8 and 14%, depending on the specification. For software, the magnitudes are smaller, with declines of 7-11% and 2-6%, respectively. I address potential endogeneity from a variety of sources. Changes in product demand, such as from trade, could be affecting industries in which these technologies are used. When I compare occupations within the same industry, however, I find that the occupations exposed to software and robots have declined much more than those that are not exposed. There were large changes in skill supplies over this period, and the results are robust to controlling for skill levels. Thus, although I cannot isolate the causal effect of these technologies, the pattern of results provides suggestive evidence that they reduced employment and wages in exposed occupations.

In the final part of the paper, I apply the method to artificial intelligence. I first provide purely descriptive results on exposure. After that, I make additional assumptions that allow me to quantify artificial intelligence's potential impacts on inequality.

Patents describe artificial intelligence performing tasks such as predicting prognosis and treatment, detecting cancer, identifying damage, and detecting fraud. These are tasks involved in medical imaging and treatment, insurance adjusting, and fraud analysis, all areas that are currently seeing high levels of AI research and development. Notice that these activities are of a very different kind to those identified for robots and software. Whereas robots perform "muscle" tasks and software performs routine information processing, AI performs tasks that involve detecting patterns, making judgments, and optimization. Most-exposed occupations include clinical laboratory technicians, chemical engineers, optometrists, and power plant operators. These all involve tasks that have already been successfully automated by AI. While these are all high-skilled jobs, it is worth noting that there are also low-skilled jobs that are highly exposed to AI. For example, production jobs that involve inspection and quality control are exposed. However, these constitute a small proportion of low-skill jobs.

Consistent with these results, I find that high-skill occupations are most exposed to AI, with exposure peaking at about the ninetieth percentile. While individuals with low levels of education are somewhat exposed to AI, it is those with college degrees, including Master's degrees, who are most exposed. Moreover, as might be expected from the fact that AI-exposed jobs are predominantly those involving high levels of education and accumulated experience, it is older workers who are most exposed to AI, with younger workers much less so.

These descriptive results clearly indicate that AI will affect very different occupations, and so different kinds of people, than software and robots. Without imposing additional assumptions, however, I cannot say what these impacts will be, or even whether they will be positive or negative. Thus, to quantify AI's potential impacts on inequality, I end the paper by making the strong assumption that the relationship between AI exposure and changes in wages will have the same sign, and the same linear relationship, as for software and robots. Under this assumption, I calculate the wage distribution for different potential magnitudes of the relationship between AI exposure and wage changes. I find that AI is projected to reduce inequality measured as the ratio of the 90th to the 10th percentile of wages. On the other hand, it is projected to increase inequality at the top of the distribution, measured as the ratio of the 99th to the 90th percentile. Applying the estimated software coefficient to AI, I project a 4% decrease in 90:10 inequality; using the robot coefficient, the decrease is 9%.

These results should be interpreted with caution. First, they rely on a constant mapping between exposure and changes in demand. In the context of the model, I am assuming that the structural parameters remain constant. Based on the results of the case studies, this seems a reasonable prior, though the evidence is only suggestive. Second, there are a number of measurement issues, particularly concerning top earners, that mean my results may understate the impacts on inequality. Third, I cannot rule out that AI will produce impacts other than via task-level substitution, such as via new tasks and purely labor-augmenting technical change. To affect my results, the distribution of impacts on labor demand due to these other channels would need to be correlated with the distribution of impacts due to substitution. While I cannot rule this out, there is no strong a priori reason to expect it to be the case.

Fourth, there is the question of timing. It is too early in the development of AI to know how much more of the technology there is to be developed, and too early also to know how long it will take to be adopted. The results in this paper concern only the applications of artificial intelligence that have been described in patents to date. Finally, this paper's results do not describe what happens to individuals in exposed occupations. For example, individuals in occupations exposed to software and robots that saw decreases in demand could have suffered wage declines or unemployment, or they could have moved to different jobs for which demand was strong. Edin et al. (2019) find that individuals in shrinking occupations see substantial wage penalties and increases in unemployment, suggesting that, on average, negative occupation impacts translate into negative individual impacts.

This paper makes three contributions to the literature. The first contribution is a general-purpose measurement of technology. Many influential papers have constructed careful measures of exposure to particular technologies.[2] These measures are all "ad hoc", having been manually created to capture individual economists' subjective understanding of the nature of particular technologies. This requires substantial technical knowledge on the part of the economist, and such knowledge is hard to acquire for frontier technologies. The measure developed in this paper, by contrast, is objective, easy to replicate, and can be applied to any technology, including both those whose impacts have already occurred, and those whose impacts lie mostly in the future.

The second contribution is to the literature on the impacts of automation on jobs and wages. A large literature studies the relationship between adoption of particular technologies and labor market impacts.[3] These papers tend to study a single technology, often using data that is only at the industry level, or at the firm level within a single sector. A contribution of this paper is to apply the same methodology consistently across several different episodes of technological change, across the whole economy, using the same research design. A key result that emerges from this exercise is that technologies are very different from each other, and so impact very different kinds of people. However, the exercise also produces suggestive evidence that the relevant structural parameters could be somewhat constant over time, making it possible to predict the impacts of new technologies based on their capabilities.

Finally, this paper contributes to a burgeoning literature that tries to predict the impacts of AI specifically.[4] This literature relies on expert surveys, usually of computer scientists. With new technologies such as AI, experts have had little time to understand the full range of the technology's potential use cases in different areas of the economy. As Brynjolfsson and Mitchell have written

[2]For example, Autor, Levy, and Murnane (2003), Acemoglu and Autor (2011), Autor and Dorn (2013), and Graetz and Michaels (2018).

[3]For IT, see, for example, Krueger (1993) and Michaels, Natraj, and Van Reenen (2013); for broadband, Akerman, Gaarder, and Mogstad (2015); and for robots, Graetz and Michaels (2018) and Acemoglu and Restrepo (2017). A paper that uses a more general measure of automation is Bessen et al. (2019).

[4]Examples include Frey and Osborne (2017), Arntz, Gregory, and Zierahn (2017) , Grace et al. (2017), Manyika et al. (2017), Brynjolfsson, Mitchell, and Rock (2018), and Felten, Raj, and Seamans (2017).

(Bryniolfsson and Mitchell 2017), there is "no widely shared agreement on the tasks where ML systems excel, and thus little agreement on the specific expected impacts on the workforce and on the economy more broadly." The measure developed in this paper offers a broad, objective answer to this question by aggregating the knowledge and ideas of inventors and companies patenting in every area of the economy. Moreover, because it is fully automated, it can be re-calculated continuously to incorporate new applications of AI as they are developed.

The rest of this paper proceeds as follows. In Section I, I outline the model and discuss the economics of automation more broadly. In Section 2, I describe the data used. Section 3 describes the method for calculating exposure scores. Section 4 describes the robots case study, while Section 5 describes the software case study. Section 6 turns to AI. Section 7 concludes.

1 Model

There are many channels through which a technology can affect labor demand. Understanding these channels is important for interpreting the empirical analyses that use my measure in the rest of the paper. In this section, I develop a simple model that illustrates some of the most important channels, and briefly discuss a number of other considerations.

1.1 Model setup

I develop a simple, static task-based model in the spirit of Acemoglu and Restrepo (2018). In that model, the economy produces a unique final good by combining tasks in a CES production function. Some tasks can be technologically automated, while others can only be performed by humans.

My model departs from Acemoglu and Restrepo (2018)'s in that I add occupations as a unit of analysis. My measure of automation exposure is at the occupation level, so understanding how technology affects demand for occupations is crucial for establishing what we can learn from my measure. It is important, too, for studying technology's distributional consequences. Whereas Acemoglu and Restrepo (2018)'s focus is on the labor share overall, mine is on how technology differentially affects different parts of the labor market. Occupations are the most natural unit through which to analyze this.[5]

[5]Another difference is that in Acemoglu and Restrepo (2018), the set of tasks is not fixed, so that new tasks may replace old tasks. In my model, I fix the set of tasks. This simplification makes the analysis more tractable. It also more closely matches my empirical setting, since I do not measure the reallocation of tasks across occupations. I discuss this issue further below.

1.2 Environment

The economy consists of a single firm that produces a unique final good.[6] The firm produces the good, X, by combining the output of different occupations, O_i, in a constant elasticity of substitution production function with elasticity parameter ρ:

$$X = \left(\sum_i \alpha_i O_i^{\rho} \right)^{\frac{1}{\rho}}.$$

Each occupation, O_i, produces its output by combining the output of a number of tasks. These tasks are denoted $T_{i,j}$, where j indexes tasks. The task outputs are combined in another constant elasticity of substitution production function with a different elasticity parameter, ρ_t (t is for "task"):

$$O_i = \left(\sum_j \alpha_j T_{i,j}^{\rho_t} \right)^{\frac{1}{\rho_t}}.$$

Some of these tasks can be automated, while others cannot. Tasks that are automated can be performed either by humans, H, or machines, R. [7] Humans and machines are perfect substitutes at the task level. Tasks that are not automated can be performed only by humans:

$$T_{i,j} = \begin{cases} H_{i,j} + A_{i,j} R_{i,j} & \text{if automation feasible;} \\ H_{i,j} & \text{otherwise.} \end{cases}$$

Human productivity is normalized to one. However, machine productivity can increase over time (for a given feasible task). I denote machine productivity by $A_{i,j}$.

The firm takes the wage of human labor in occupation O_i, w_i, as given. Similarly, it takes as given the rental rate of a machine, r. Clearly, in this setup, the firm will employ exclusively human labor for task j in occupation i if $w_i < \frac{r}{A_{i,j}}$, and exclusively machines if the inequality is reversed. A task's being infeasible to automate is therefore equivalent to $A_{i,j} = 0$.

1.3 Impact of automation on labor demand

How does a change in machine productivity affect the firm's demand for human labor by occupation? First, consider a setup in which there is a single occupation with two tasks, only one of which can

[6] The assumption of a single firm is not substantive. It would be easy to write the model with many firms; I discuss a model with many industries below.

[7] To fix ideas, one can think of R as corresponding to robots; however, R here refers to any kind of automation technology.

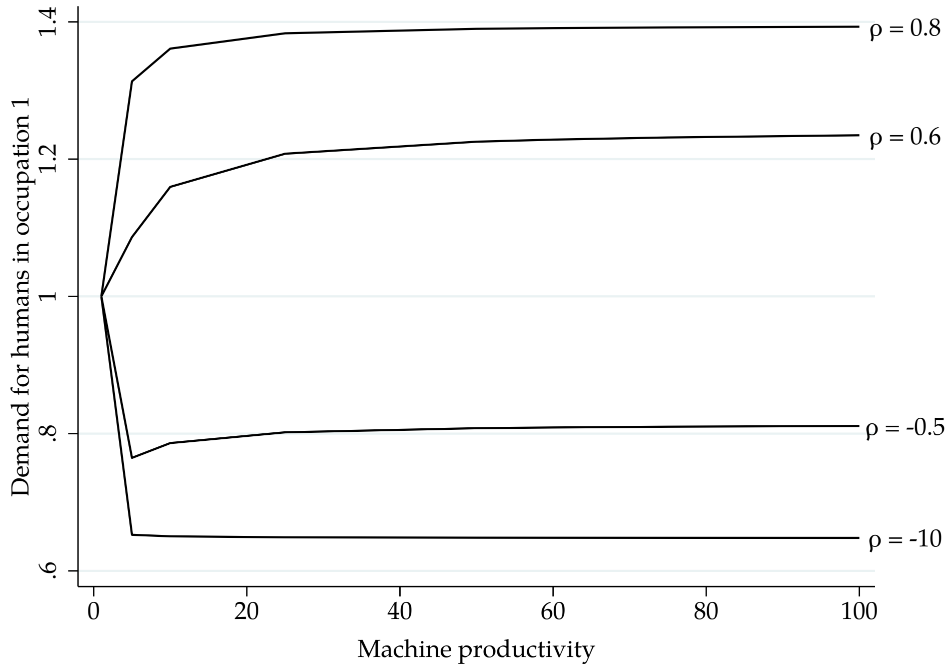


Figure 1: Model simulation results: demand for humans in occupation 1 (occupation being automated) as a function of robot productivity, for different values of firm-level elasticity of substitution parameter ρ. Task-level elasticity of substitution parameter ρ_t is fixed at -10.

be automated. There are two levels of demand to consider: the firm's demand per unit of output, and the total units of output demanded by consumers. As machine productivity increases, the firm's demand for human workers per unit of output will unambiguously decrease. The human workers will be fully displaced from the automatable task; to the extent the two tasks are substitutes, fewer human workers will be demanded to perform the non-automatable task too. However, this automation reduces the cost of the final good, and hence its price, leading consumers to demand more of it.[8] This increase in final demand offsets the reduction in per-unit labor demand, and could even lead to a net increase in labor demand. This scenario has been developed in detail in the literature. For example, Bessen (2015) argues that ATMs, which automate some of the tasks of bank tellers, increased demand for that occupation by reducing the cost of opening new bank branches. While bank tellers per branch decreased, banks opened sufficiently many new branches that the overall number of tellers increased.

To bring an additional channel into focus, consider a setup with two occupations, in which each occupation consists of two tasks. In the first occupation, one task can be automated, while the other can only be performed by a human. In the second occupation, neither task can be automated.

[8]These two effects are analogous to what Acemoglu and Restrepo (2018) call the "displacement" and "productivity" effects, respectively.

Figure 1 displays firm demand for the first occupation as the machine productivity parameter $A_{1,1}$ increases from 1, which is equal to human productivity, to 100. The task-level elasticity parameter is set to $\rho_t = -10$, so that tasks are complements in production. Each line corresponds to a different value of the firm-level elasticity parameter, from $\rho = -10$ (occupations are strong complements) to $\rho = 0.8$ (occupations are strong substitutes).

The figure shows that when the two occupations are highly substitutable, the firm's cost-minimizing choice is to demand relatively more of occupation 1, the occupation that has been partially automated. The intuition for this is simple. Because the level of machine productivity is high, this increases the productivity of occupation 1, leading the firm to demand more of it. The tasks within occupation 1 are complements, however, so the firm still needs to hire lots of humans to perform the human-only task. For $\rho > 0.5$, this channel is sufficiently strong to cause a net increase in the firm's demand for human workers in occupation 1 — even though this occupation is the one that is being automated. As an example of occupations that are substitutes, consider operations analysts and industrial technicians, both of which improve efficiency on a factory floor. The operations analysts develop mathematical models of the factory and simulate them. It is easy to see how automation of the simulation task could make the operations analysts so much more productive that the firm would hire more operations analysts and fewer industrial technicians per unit of output. Note that this effect is driven entirely by the substitutability of occupations in production, and has nothing to do with the elasticity of consumer demand.[9]

1.4 Discussion and implications for empirical analysis

The analysis so far has illustrated displacement and productivity effects in an economy with a single firm. The productivity effect operates at two levels. Inside the firm, the substitutability of occupations in production affects how automation changes the firm's demand for occupations per unit of the final good produced. Outside the firm, price changes affect consumers' demand for the final good. Overall, then, the impact of task-level automation on the demand for occupations is theoretically ambiguous. Without making strong restrictions on the various elasticity of substitution parameters, it is impossible to sign the direction of impacts.

The method I develop in this paper allows me to identify the tasks for which technology can substitute for human labor. I am therefore able to estimate empirically the relationship between the extent to which an occupation's tasks can be replaced by technology and changes in demand for that occupation. Given the theoretical ambiguity of the model, this is an interesting question in its own right. It will also be informative about how much we can learn from the measure about

[9] Of course, the consumer demand channel also operates in this setting.

the potential impacts of AI. In the rest of this paper, I analyze two historical case studies, and find that, in both, there is a negative relationship between my measure and changes in employment and wages by occupation. This shows that the balance of forces favored substitution in the past, and may move our priors toward thinking that the same will be true in the future.

To further set the stage for the empirical analysis, several extensions to the model merit attention. First, consider an economy with multiple industries. Industries employ different combinations of occupations, which have different opportunities for automation. Automation in one industry changes the relative prices of the final goods of all industries. This change in relative prices leads consumers to change their consumption bundles. If preferences are nonhomothetic, moreover, automation also causes demand changes due to wealth effects. Because different industries employ different occupations, these changes in final demand affect occupation demand. To handle this complexity, I confine most of my analysis to studying within-industry changes in the relative demand for occupations. This helps to isolate those changes in demand for occupations that are due to task-level substitution on the production side, the chief object of my analysis, rather than those due to changes in consumers' incomes and the prices they face.

Second, there is a richer set of ways that technology can impact production. In addition to automating existing tasks, technology can create entirely new tasks. These tasks can be ones involved in producing new goods, or the result of an increase in the scope of occupations in existing industries. Technology can also induce the reorganization of tasks among occupations. Finally, it can create purely factor-augmenting technological change.[10]

Are these other demand-side factors likely to bias my results? It seems likely that the technologies studied in this paper may produce, for example, purely labor-augmenting technical change that advantages some types of labor over others. For these to affect my conclusions about the occupations harmed due to task-level substitution, however, the distribution of impacts on labor demand due to labor-augmenting technical change would need to be correlated with the distribution of impacts due to substitution. A priori, there is no strong reason to expect this to be so. The example of software offers some empirical support for this idea. Autor, Levy, and Murnane (2003) show that software complements tasks with high abstract content, and substitutes for tasks with high routine content. How much do these different types of task content overlap within occupations? Regressing one measure on the other, I find that the variation in the routine task content of occupations

[10] All of these can be seen in the example of the steamship, which replaced sailboats in the late nineteenth century (Chin, Juhn, and Thompson 2006). The steamship was a new good, with a different production process from sailboats. Consumers substituted away from sailboat transportation into steamship transportation. This reduced demand for mariners who were skilled in handling a ship's sails, but not by automating sail handling. It created new tasks, such as tending the steamship's engines and shoveling coal into its boiler, and reorganized the tasks done by existing seafaring occupations. Finally, improvements in the efficiency of the steam engine were a form of pure capital-augmenting technological change.

explains only 2% of the variation in their abstract task content. This suggests that "routineness" is independently useful as a measure of potential displacement due to software, and that its usefulness is not diminished by the existence of other types of tasks that software complements. Indeed, a large literature on "routine-biased technical change" has used measures of routineness for just this purpose. The other factors, such as new tasks and endogeneous occupational scope, are subject to much ongoing research. Insofar as substituted tasks within an occupation are replaced by new tasks that increase demand for the occupation, this will attenuate my results.

Finally, consider workers' occupational choices and human capital investments. If the supply of each occupation is fixed, reductions in demand affect only wages. If, instead, workers can change occupations, then changes in demand can affect both employment and wages. This has important implications for welfare. For example, suppose that radiologists and truck drivers are equally exposed to automation. Suppose further that radiologists have highly specialized human capital, such that no other occupation open to them pays close to their current wage, whereas truck drivers have many outside options that pay a similar wage to their current job. In this case, because of their different outside options, radiologists would see much greater reductions in wages due to automation than truck drivers, even though both were equally exposed to automation.

Will my results, then, be informative about the incidence of these technologies? In the absence of longitudinal data that allows me to follow individuals over time, there is a limited amount I can say. However, other work offers suggestive evidence. Edin et al. (2019) use administrative data from Sweden to show that workers who faced occupational decline over the period 1986-2013 saw substantial declines in lifetime earnings. If a similar pattern holds in the US, then my occupation-level results will point towards the individuals who are harmed by this task-level substitution. Research using longitudinal data from the US is thus a priority for future research.

2 Data

The method for constructing my measure of the exposure to occupations requires two sources of text: patents and job descriptions. The main empirical results require data on employment and wages for occupation-industry cells, as well as various controls.

2.1 Patent data

I use Google Patents Public Data, provided by IFI CLAIMS Patent Services.[11] The fields I use are the title, abstract, and CPC codes, as I describe further below.

[11]Data accessed via Google BigQuery at https://console.cloud.google.com/marketplace/details/google_patents_public_datasets/google-patents-public-data.

2.2 Job descriptions data

For job descriptions, I use the O*NET database of occupations and tasks. This database is produced by an agency of the US Department of Labor, and is the successor to the Dictionary of Occupational Titles (DOT). These dictionaries were originally created in the 1930s to "furnish public employment offices... with information and techniques that will facilitate proper classification and placement of work seekers" (U.S Employment Service 1939). O*NET describes 964 occupations. A set of tasks is listed for each occupation, described in natural language. For example, a doctor's task is "interpret tests to diagnose patient's condition". Occupations and tasks have various additional metadata, such as numerical scores indicating interpersonal or analytical skills required. These metadata have been widely used by economists.[12] For this paper, I just use the text itself. Each task is also given scores that indicate its importance and frequency in the occupation. I use these scores to weight tasks within occupations.

2.3 Employment/wage data (Census/ACS)

To measure the relationship between my measure and changes in wages and employment, I use individual-level microdata from the US Census 1960-2000 and from the ACS 2000-2018, provided by IPUMS (Ruggles et al. 2019). For my main analysis sample, I restrict to individuals in work between the ages of 18 and 65, and calculate average wages and the proportion of hours worked in each industry-occupation cell. I use various other Census variables for controls and additional analyses, such as age, gender, and level of education. I use the measure of offshorability developed by Firpo, Fortin, and Lemieux (2011) and standardized in Autor and Dorn (2013), and the measure of occupational licensing developed by Kleiner and Xu (2017). For all these analyses, I use the "occ1990dd" occupational classification developed by Dorn (2009) and extended by Deming (2017), and the IPUMS "ind1990" industry classification. Full details are provided in Appendix B.

3 Method

In this section, I describe how I construct a new, objective measure of the exposure of tasks to automation by quantifying the overlap between the text of patents and the text of job descriptions. In the following sections, I construct my measure and study its performance separately for each technology case study.

[12] Examples include Howell and Wolff (1991), Autor, Levy, and Murnane (2003), and Deming (2017).

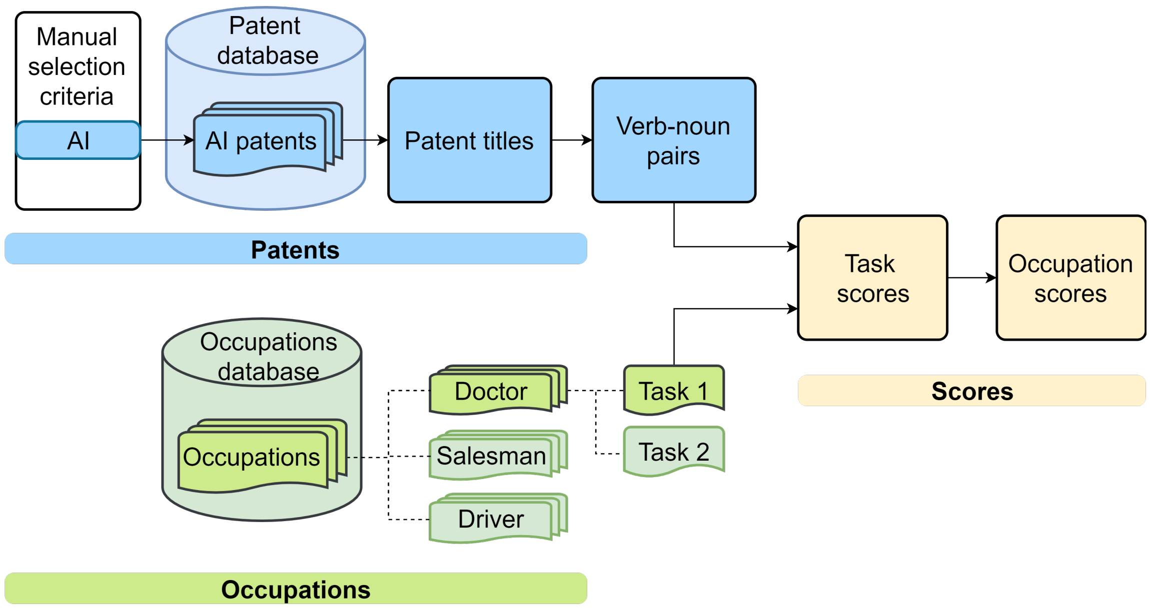


Figure 2: Illustration of process for constructing technology exposure measures

3.1 Overview

To assess the exposure of occupations to a given technology, I use the text of patents to identify what the technology can do, then quantify the extent to which each occupation in the economy involves performing similar tasks. The method is depicted in Figure 2.

On the patent side, I first choose the set of patents corresponding to a particular technology. For example, I define the set of artificial intelligence patents as those that use certain keywords, such as “neural network”, in their titles or abstracts. I extract all the titles from this set of patents. Such patent titles might include “Method for diagnosing diseases” and “Method for recognizing aircraft”. From this list of titles, I extract all verb-noun pairs. This results in a long list of pairs, such as (diagnose, disease), (recognize, aircraft), and so on. For each pair, I calculate how often that pair, or ones similar to it, occurs in the list of all pairs. (I explain how I group “similar” pairs below.) For example, pairs similar to (diagnose, disease) might represent 0.1% of all pairs extracted from the titles of my set of artificial intelligence patents.

I now turn to occupations. In my database of occupations, any given occupation, such as “doctor”, consists of a collection of tasks. Each task is described in free-form text, such as “Interpret tests to diagnose patient’s condition”. From each task description, I extract all verb-noun pairs. For the task just mentioned, the pairs would be (interpret, test) and (diagnose, condition). Most occupations have 20-40 extracted pairs in total. To each pair, I assign the relative frequency of similar pairs in my patent titles. For example, if pairs similar to (diagnose, condition) represented 0.1% of all pairs extracted from the titles of my set of artificial intelligence patents, I would assign a score of

0.001 to that verb-noun pair. To get a single overall exposure score for the "doctor" occupation, I take an average of all the verb-noun pairs mentioned in the task descriptions of that occupation, weighted by the "importance" of the task to the occupation (defined below).

3.2 Extracting verb-noun pairs from patents

I select patent publications corresponding to each technology from the Google Patents Public Data database using keyword searches of patent titles and abstracts, and CPC codes. The search criteria for each technology, and how they were chosen, are described in the corresponding case study section below. I restrict my search to the earliest-filed published patent document within each patent family.

I extract verb-noun pairs from patent titles. I use only titles because they have a much higher signal-to-noise ratio than the other patent text fields. Specifically, a patent's title tends to express the main application of the invention, whereas the abstract, description, and claims contain technical implementation details that are irrelevant for my purposes.

To extract verb-noun pairs from any given sentence (such as a patent title), I perform the following sequence of steps. First, I use a dependency parsing algorithm (Honnibal and Johnson 2015) to determine the syntactic relations of the words in the sentence. This algorithm attains 91.85% accuracy on the standard dependency parsing benchmark used in the natural language processing literature. Next, for each verb, I select its direct object as identified by the algorithm, if it exists, and store the resulting pair. I then lemmatize the verb, so that, say, "predicting" and "predicted" are both recorded as "predict"; and lemmatize the noun, so that, say, "person" and "people" are both recorded as "person". Stop words such as "use" and "have", which do not express economic applications, are dropped, as is common in the natural language processing literature (Jurafsky and Martin 2014). Note that the entire process just described is fully automated. Examples of titles of artificial intelligence patents, and corresponding verb-noun pairs, are displayed in Table A1.

3.3 Measuring overlap

I use the O*NET database, produced by the US Department of Labor, as my source of information on occupations. As noted above, each occupation consists of a collection of tasks described in natural language. Table 1 illustrates some of the component tasks of precision agriculture technicians, an occupation that I will find has high exposure to artificial intelligence. For each task, such as "analyze geospatial data to determine agricultural implications of [various factors]", I use the same dependency parsing algorithm as for patents to extract verb-noun pairs. The table displays these extracted pairs for each task. Figure A1 in the appendix plots the distribution of the number of

Table 1: **Tasks and exposure scores for precision agriculture technicians.**

Task	Weight in occupation	Extracted pairs	AI exposure score x100
Use geospatial technology to develop soil sampling grids or identify sampling sites for testing characteristics such as nitrogen, phosphorus, or potassium content, ph, or micronutrients.	0.050	(develop, grid)	0.050
		(identify, site)	0.234
		(test, characteristic)	0.084
Document and maintain records of precision agriculture information.	0.049	(maintain, record)	0.000
Analyze geospatial data to determine agricultural implications of factors such as soil quality, terrain, field productivity, fertilizers, or weather conditions.	0.048	(analyze, datum)	0.469
		(determine, implication)	0.837
Apply precision agriculture information to specifically reduce the negative environmental impacts of farming practices.	0.048	(apply, information)	0.000
		(reduce, impact)	0.151
Install, calibrate, or maintain sensors, mechanical controls, GPS-based vehicle guidance systems, or computer settings.	0.045	(maintain, sensor)	0.000
Identify areas in need of pesticide treatment by analyzing geospatial data to determine insect movement and damage patterns.	0.038	(identify, area)	0.234
		(analyze, datum)	0.469
		(determine, movement)	0.502

Notes: Table displays six of the twenty-two tasks recorded for precision agriculture technicians in the O*NET database. For each task, the weight is an average of the frequency, importance, and relevance of that task to the occupation, as specified in O*NET, with weights scaled to sum to one. The verb-noun pairs in the third column are extracted from the task text by a dependency parsing algorithm. The AI exposure score for an extracted pair is equal to the relative frequency of similar pairs in the titles of AI patents. The score multiplied by 100 is thus a percentage; for example, pairs similar to "determine implications" represent 0.84% of pairs extracted from AI patents.

verb-noun pairs extracted across occupations. The vast majority of occupations (92%) have more than 15 extracted pairs in total, and most (76%) have more than 20 extracted pairs.

Before calculating an exposure score for each verb-noun pair, I first group the nouns in each pair into conceptual categories. I do this because the nouns used in O*NET task descriptions are quite general, whereas the nouns used in patents vary in their generality. For example, if an O*NET task verb-noun pair refers to "animals", and a patent verb-noun pair refers to "mammals", I want to account for the fact that "mammal" is an instance of "animal". This would not be possible using a thesaurus, since "mammal" and "animal" are not synonyms.

Instead, I use WordNet (Miller 1995), a database developed at Princeton University that groups nouns into a hierarchy of concepts. For example, the ancestors of "economist" are "social scientist", "scientist", "person", "causal agent", "physical entity", and "entity". At each conceptual level, the conceptual categories are mutually exclusive. This allows me to assign each of the nouns occurring in my verb-noun pairs to a single conceptual category, for a given conceptual level. I use "aggregated verb-noun pair" to refer to a pair consisting of a verb and a noun conceptual category. For the conceptual level that includes "person", for example, "recognize economist" would be part of the aggregated verb-noun pair "recognize person".

In choosing the conceptual level at which to group the nouns, I face a trade-off between specificity and coverage. For example, if I group into categories at the conceptual level of "dog", I lose all words that exist only at a more general level, such as "mammal" and "animal". Figure A3 in the appendix displays the share of verb-noun pairs extracted from O*NET tasks that would be lost for this reason at each level of aggregation. Due to the level of generality at which O*NET tasks are expressed, I would lose more than a quarter of all verb-noun pairs if I grouped at WordNet level 5, for example. (Levels with higher numbers are more specific.) I therefore use WordNet level 3 for my main results, and re-run my analyses at levels 2, 4, and 5 to check their sensitivity. While the level of aggregation does make some difference, the results for these other levels are qualitatively very similar to my baseline specification.

3.4 Measuring the exposure of occupations

I now describe how I calculate an occupation's final exposure score using the set of aggregated verb-noun pairs extracted from its task descriptions. Denote the set of technologies T. For a given technology, $t \in T$, let f_c^t denote the raw count of occurrences of aggregated verb-noun pair c extracted from technology t patent titles, and let C^t denote the full set of aggregated verb-noun pairs for technology t. The relative frequency, rf_c^t, of aggregated verb-noun pair c in technology t patent titles is

$$rf_c^t = \frac{f_c^t}{\sum_{c \in C^t} f_c^t}.$$

I assign to each of the task-level aggregated verb-noun pairs that pair's relative frequency, rf_c^t, in technology t patent titles. These scores for artificial intelligence are displayed in the final column of Table 1.

For each occupation i, I then take a weighted average of these task-level scores to produce an overall technology t exposure score for the occupation,

$$Exposure_{i,t} = \frac{\sum_{k \in K_i} \left[w_{k,i} \cdot \sum_{c \in S_k} rf_c^t \right]}{\sum_{k \in K_i} \left[w_{k,i} \cdot |\{c : c \in S_k\}| \right]}.$$

In this expression, K_i is the set of tasks in occupation i, and S_k is the set of verb-noun pairs extracted from task $k \in K_i$. Finally, $w_{k,i}$, the weight of task k within occupation i, is an average of the frequency, importance, and relevance of task k to occupation i, as specified in the O*NET database, with weights scaled to sum to one.

An occupation's exposure score for technology t thus expresses the intensity of patenting activity in technology t directed towards the tasks in that occupation. Figure A2 in the online appendix shows the distribution of AI scores across occupations.

4 Application: Robots

In this section, I apply the method to a first historical case study: robots. After some brief background, I describe the construction of the measure for robots, and present the key results, including most and least exposed tasks and occupations. I then present descriptive evidence on the distributional impact of robots. The section concludes with an analysis of the relationship between exposure and changes in wages and employment.

4.1 Background and definition

This case study focuses on industrial robots. Industrial robots are robots used in manufacturing, rather than robots used, for example, in surgery, or in other parts of the service sector. The reason for the restriction is that industrial robots have seen by the far the most adoption, whereas service sector robots are more nascent. Industrial robots also have a standardized definition, ISO 8373, that is used for constructing measures of adoption. Robots are defined as "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications." A manipulator is defined as a "machine in which the mechanism usually consists of a series of segments, jointed or sliding relative to one another, for the purpose of grasping and/or moving objects (pieces or tools) usually in several degrees of freedom." Examples of robots fitting this definition include manipulators that weld or paint cars, load and unload workpieces from factory equipment such as CNC machine tools and semiconductor fabricators, move materials, and pack boxes. Examples of pieces of industrial equipment that are not robots include most machine tools, an assembly line conveyor belt, and a flexible manufacturing cell (although these latter two may be tended by robots).

4.2 Patent selection

To calculate exposure scores for robots, I first define the set of patents that represent applications of industrial robots. In an ideal world, I would have manually looked through every patent in the database and carefully read it to see whether it corresponded with the ISO definition of industrial robot. Since there are many millions of patents, this exercise was infeasible. As such, I instead followed the following procedure, designed to achieve something as close to the ideal procedure as possible. First, some RAs and I manually compiled a set of 100 patents, with 50 that we deemed to correspond to the ISO robot definition, and 50 that we deemed not to do so. We labeled each patent independently, and then discussed examples on which we disagreed to reach a resolution. We used the Google Patents search engine to find the example patents, using various keyword searches featuring words in or similar to those in the ISO definition.

With our set of positive and negative example patents in hand, we generated a list of candidate keywords and CPC codes that could constitute elements of search queries. The elements could be either inclusion or exclusion criteria for patent titles, abstracts, and CPC codes (e.g., include if the abstract contains "manipulator", exclude if it contains "surgery"). We generated this set of criteria by studying the ISO definition, other patents we found using the Google Patents search engine, and relevant books and trade journal articles. We then selected patents according to every possible Cartesian combination of all our search criteria, and assessed each selection against our test set. We chose the one with the highest F1 score (the harmonic mean of precision and recall) on our test set. The final search criteria used was that the title and abstract should include "robot" OR "manipulat", and that the patent's list of CPC codes should not include A61 ("medical or veterinary science; hygiene") or B01 ("physical or chemical processes or apparatus in general").

Table 2: **Top extracted verbs and characteristic nouns for robots.**

Verb	Example nouns	Verb	Example nouns
clean	surface, wafer, window, glass, floor, tool, casting, instrument	**walk**	robot, structure, base, stairs, circuit, trolley, platform, maze
control	robot, arm, motion, position, manipulator, motor, path, force	**carry**	substrate, wafer, tray, vehicle, workpiece, tool, object, pallet
weld	wire, part, tong, electrode, sensor, component, nozzle	**detect**	position, state, collision, obstacle, force, angle, leak, load, landmine
move	robot, body, object, arm, tool, part, substrate, workpiece	**drive**	unit, wheel, motor, belt, rotor, vehicle, automobile, actuator

Notes: This table lists the top eight verbs by pair frequency extracted from the title text of patents corresponding to robots, together with characteristic direct objects for each verb chosen manually to illustrate a range of applications. Patents corresponding to each technology are selected using a keyword search. A dependency parsing algorithm is used to extract verbs and their direct objects from patent titles.

4.3 Measurement results

Top verb-noun pairs from patents Table 2 presents the most frequent verbs and illustrative nouns extracted from the robot patents. They include cleaning floors, surfaces, and instruments; moving arms, substrates, and workpieces; welding wires and parts; detecting surfaces, loads, and mines; and assembling vehicles, cabinets, and windshields. These correspond to a wide variety of major applications of robots, particularly in semiconductor and automobile manufacturing, two industries that have seen major adoption of robots.

There are also some verb-noun pairs that likely reflect noise in the measure, such as cleaning a robot, controlling an actuator, and detecting a load. For the most part, this noise seems unlikely to affect the results, since job descriptions do not mention such robotically instrumental activities. However, it is possible that some human tasks, such as those involving cleaning, will receive higher scores than they "ought" to because of, for example, the semantic similarity between cleaning a robot and cleaning other things.

Most and least exposed occupations Table 3 displays the five occupations most exposed to robots, and the five occupations least exposed. I find that the most-exposed occupations include various kinds of materials movers in factories and warehouses, and tenders of factory equipment. Many of these occupations have in fact seen robot-driven automation. For example, one might naively expect both truck driving and forklift truck driving to be automated, given they involve similar activities. However, the method correctly identifies that forklift truck driving (i.e., materials moving

Table 3: **Occupations with highest and lowest exposure to robots.**

Most exposed occupations	Least exposed occupations
Forklift driver	Payroll and timekeeping clerks
Operating engineers of cranes, derricks, etc.	Art/entertainment performers
Elevator installers and repairers	Clergy
Janitors	Correspondence and order clerks
Locomotive operators: engineers and firemen	Eligibility clerks for government programs

Notes: Table displays census occupation title for the five occupations with the highest exposure scores and with the lowest exposure scores above employment threshold of 150.

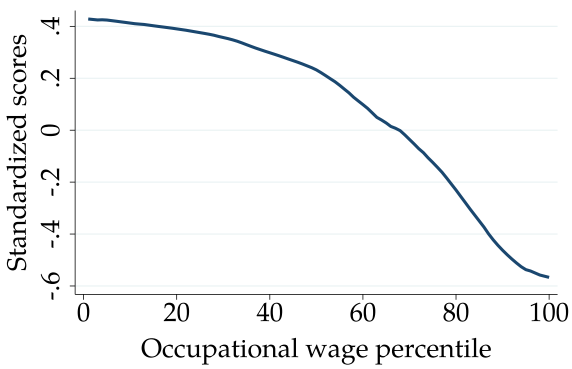
in warehouses and factories) has been heavily automated by robots, while road truck driving has not. (To the extent road truck driving is being automated currently, this automation is not being done by industrial robots as defined here.) Least-exposed occupations include payroll clerks, artistic performers, and clergy. These do not primarily involve the kinds of repetitive manual tasks that robots automate.

The noise in the measure creates some false positives. For example, a highly-exposed occupation is "elevator installers and repairers". It receives a high score because its tasks feature assembling and welding elevator cars. The algorithm extracts the word "cars" as the noun in the verb-noun pair, rather than "elevator cars", and so assigns a high score based on the large number of car welding and assembly robots patents.

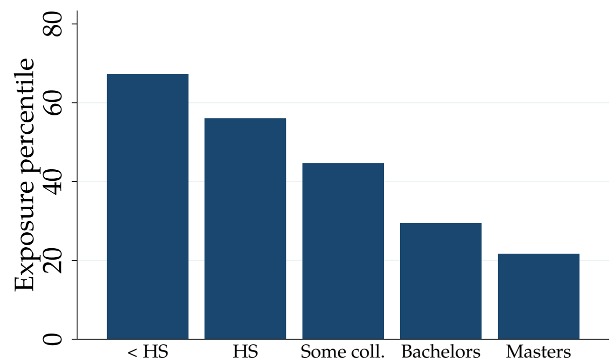
4.4 Distributional impacts of robots: descriptive evidence

I now turn to consider the distributional impacts of robots, by studying the kinds of people who work in occupations highly exposed to robots. To each individual in the IPUMS 2010 census sample, I assign the exposure score of the their occupation. I then create two kinds of results. In the first kind, I look at particular demographic groups, such as individuals with different levels of education, and calculate the average exposure scores of these individuals given their occupations. In the second kind, I use occupations as the unit of analysis. I rank occupations by, for example, the percent of workers who are female, or by their average wage, and plot exposure scores against these rankings.

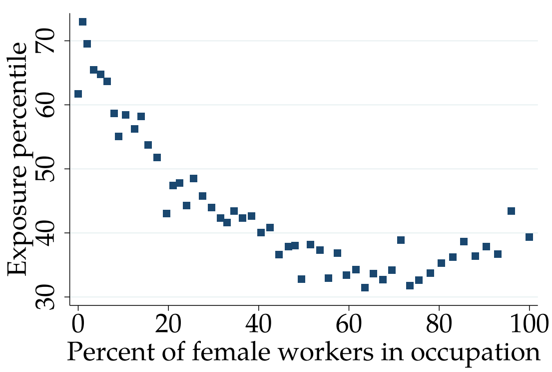
The results are presented in Figure 3. Panel (a) plots exposure scores against occupational wage percentiles, with percentiles weighted by hours worked. This figure shows that low-wage occupations are most exposed, and high-wage occupations much less. Panel (b) presents exposure scores by individuals' levels of education. Individuals with less than high school education are most exposed to robots. Exposure decreases monotonically by level of education, with almost no



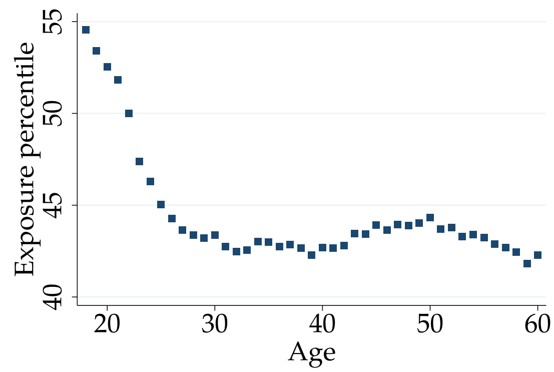
(a) Smoothed scores by occupational wage percentile



(b) Exposure by level of education



(c) Exposure by percent of female workers in occupation



(d) Exposure by age.

Figure 3: **Exposure to robots by demographic group**

Notes: Plot (a) shows the average of standardized occupation-level exposure scores for robots by occupational wage percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), following Acemoglu and Autor (2011). Wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean hourly wage in the May 2016 Occupational Employment Statistics. Plot (b) is a bar graph showing the exposure score percentile for robots averaged across all industry-occupation observations, weighted by 2010 total employment in given educational category. Plot (c) is a binscatter. The x-axis is the percent of workers in an industry-occupation observation reported female in the 2010 census. Plot (d) is a binscatter. The x-axis is the average age of workers in an industry-occupation observation in the 2010 census.

exposure for those with master's degrees. This is consistent with the results by occupational wage percentile.

Panel (c) plots average exposure scores for occupations by percent of female workers. This shows that occupations whose workers are predominantly male are much more exposed to robots than occupations with a primarily female workforce. This is consistent with the clustering of men in production jobs in manufacturing, which are very exposed to robots, while women are more likely to work in jobs with a high level of interpersonal content, which are much less exposed. Finally, Panel (d) shows the results by individuals' age. I find that workers in their 20s are much more likely to be exposed to robots than workers in their 30s and above. This reflects the fact that young workers are much more likely to be engaged in manual work.

It bears reiterating that in this section I am only studying the types of people who work in exposed occupations. This is different from studying what happens to those people. For example, affected individuals could have suffered wage declines or unemployment, or they could have moved to different jobs for which demand was strong. I discuss this issue further below.

4.5 Relationship between exposure and changes in wages and employment

As discussed in the model section above, the net effect of task-level substitution on demand for occupations is theoretically ambiguous, due to the countervailing productivity and displacement channels. I now study empirically the relationship between my measure of occupation exposure to robots and changes in employment and wages over the period 1980 to 2010. The overall pattern of results, for this and the other case studies, provides suggestive evidence that, over the long run, task-level substitution results in occupation-level declines in employment and wages.

4.5.1 Empirical strategy

To study the relationship between exposure scores and changes in employment and wages, I estimate variations of the following regression:

$$\Delta y_{o,i,t} = \alpha_i + \beta \mathrm{Exp}_o + \gamma \mathbf{Z}_o + \epsilon_{o,i,t}.$$

In this specification, the unit of observation is an occupation-industry-year cell, such as welders in auto manufacturing in 1980, with o denoting occupation, i industry, and t year. The dependent variable is a long difference from 1980 to 2010 of an outcome variable of interest, such as wages. On the right-hand side, I include industry fixed effects; Exp_o is the exposure of the occupation to robots; and the vector of controls $\mathbf{Z}_o$ contains occupation-level variables such as terciles of average years of education.

As described in the model section, the use of occupation-industry-year cells helps to isolate changes in the demand for occupations that are due to task-level substitution on the production side, rather than those due to changes in consumers' incomes and the prices they face. For example, trade with China has substantially reduced demand for textiles produced in the US. If I used only occupations as the unit of observation, then if there was a correlation between occupations exposed to robots and occupations in industries exposed to trade with China, I would conflate these two forces in the estimation. Instead, I study changes in relative labor demand within industries. For example, if, within textile industries, the share of textile machine operatives in employment has decreased, while that of managers has increased, this is more likely to be a function of factors affecting production, rather than factors affecting demand.

In constructing a measure of change in employment, I face issues of entry and exit of occupation-industry cells. Because of these zero-valued observations, reflecting new and obsolete jobs, I cannot use log changes. Instead, I follow the literature and use DHS changes. Also known as arc percentage change or percent change relative to the midpoint, DHS is a symmetric measure of the growth rate defined as the difference of two values divided by their average (Davis, Haltiwanger, and Schuh 1996). This results in a second-order approximation of the log change for growth rates near zero; values are restricted to being between -2 and 2, with -2 and 2 representing exit and entry respectively.

For wages, I use the log change in real weekly wages for full-time, full-year workers in each cell. For exposure scores, I transform the raw scores to be in employment-weighted percentiles. Thus, a score of 90 means that 10% of workers work in occupations with a higher exposure score. Industries are in the IPUMS IND1990 consistent industry classification; this classification is used to construct the occupation-industry cells, and also for industry fixed effects. Standard errors are clustered by industry. Finally, the sample is restricted to industries within the manufacturing sector.

4.5.2 Results

Figure 4 is a residual binscatter at the occupation-industry level showing the relationship between robot exposure and changes in employment (blue line, left axis) and changes in wages (red line, right axis), after controlling for industry fixed effects. Regression results corresponding to the binscatter are presented in Tables 4 and 5. The first column does not control for industry fixed effects; these are added in column (2). The controls added in the remaining columns are discussed below.

These results are quantitatively large. Although I cannot attribute causality to the exposure

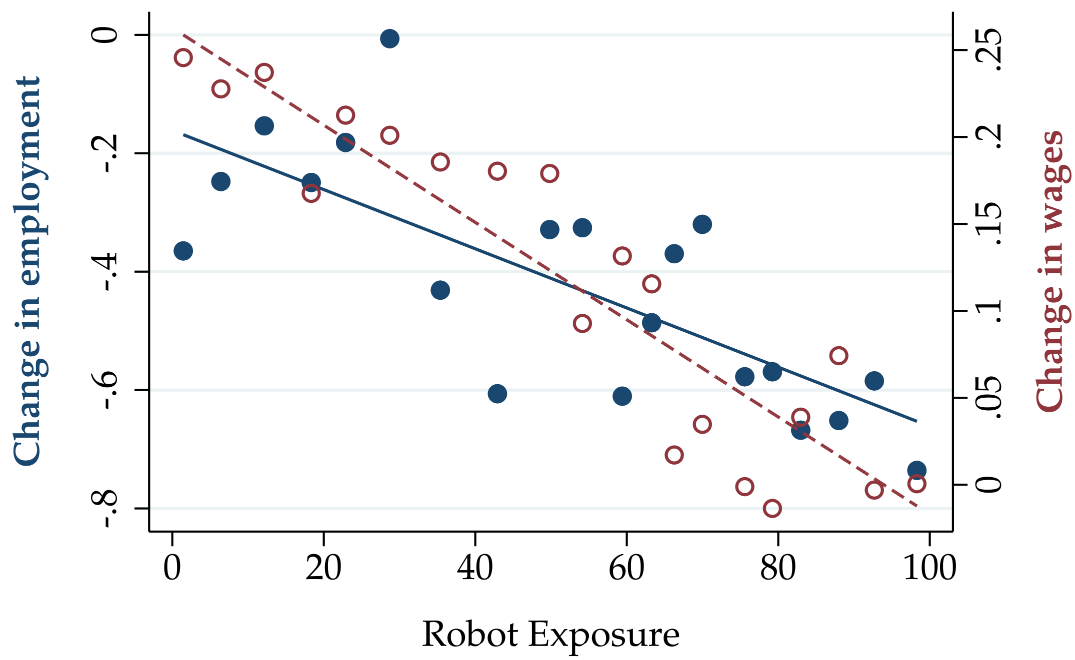


Figure 4: **Change in employment and wages 1980-2010 by exposure to robots.**

Notes: Plot is a binscatter. Change in employment is measured as DHS change of an occupation-industry cell's share of overall employment between 1980 and 2010, winsorized at the top and bottom 1%. Change in wages is measured as log difference in a cell's mean FTFY weekly wage. Controls added for industry fixed effects. Sample is restricted to industries within the manufacturing sector.

Table 4: **Change in wages vs. exposure to robots, 1980-2010.**

	(1)	(2)	(3)	(4)	(5)
Exposure	-0.29***	-0.28***	-0.26***	-0.16***	-0.22***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Offshorability			0.84*	0.82*	-2.29***
			(0.44)	(0.44)	(0.50)
Medium education				7.84***	9.52***
				(1.75)	(1.67)
High education				10.22***	27.73***
				(1.89)	(2.01)
Wage					-0.07***
					(0.01)
Wage squared					0.00**
					(0.00)
Adjusted R^2	0.042	0.094	0.095	0.101	0.163
Industry FEs		✓	✓	✓	✓
Observations	6,708	6,708	6,708	6,708	6,708

Notes: Each observation is an occupation-industry cell. Dependent variable is 100x change in log wage between 1980 and 2010 winsorized at the top and bottom 1%. Education variables are terciles of average years of education for occupation-industry cells in 1980. Wages are cells' mean weekly wage for full-time, full-year workers in 1980. Offshorability is an occupation-level measure from Autor and Dorn (2013). Sample is restricted to industries within the manufacturing sector. Standard errors are clustered by industry. * p<0.10, ** p<0.05, *** p<0.01.

scores, moving from the 25th to the 75th percentile of exposure to robots is associated with a decline in industry employment share of between 9 and 18%, depending on the specification, and a decline in wages of between 8 and 14%. Recall that these are within-industry effects. Thus, these results are not simply showing that manufacturing jobs are exposed to robots, and manufacturing has (for other reasons) declined. Rather, they show that within each manufacturing industry, the particular occupations exposed to robots have declined much more than those that are not exposed.

There are a number of potential source of endogeneity, which I now address. First, I consider the possibility that there were other changes occurring on the production side beyond robots. A major force occurring over this time period was the rise of offshoring. I control for an occupation-level index of offshorability in column (3) of the two regression tables, and find that it does not affect my

Table 5: **Change in employment vs. exposure to robots, 1980-2010.**

	(1)	(2)	(3)	(4)	(5)
Exposure	-0.37***	-0.36***	-0.35***	-0.18***	-0.16***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Offshorability			0.78	0.93*	2.02***
			(0.54)	(0.55)	(0.55)
Medium education				-0.26	-1.20
				(1.54)	(1.54)
High education				21.39***	14.42***
				(2.43)	(2.40)
Wage					0.04***
					(0.00)
Wage squared					-0.00***
					(0.00)
Adjusted R^2	0.018	0.129	0.129	0.141	0.147
Industry FEs		✓	✓	✓	✓
Observations	14,065	14,065	14,065	14,065	14,065

Notes: Each observation is an occupation-industry cell. Dependent variable is 100x DHS change of a cell's share of overall employment between 1980 and 2010, winsorized at the top and bottom 1%. Education variables are terciles of average years of education for occupation-industry cells in 1980. Wages are cells' mean weekly wage for full-time, full-year workers in 1980. Offshorability is an occupation-level measure from Autor and Dorn (2013). Observations are weighted by cell's labor supply, averaged between 1980 and 2010. Sample is restricted to industries within the manufacturing sector. Standard errors are clustered by industry. * p<0.10, ** p<0.05, *** p<0.01.

results.

Second, there changes on the product demand side that could be affecting my results. The industry fixed effects should absorb changes due to factors such as trade and shifting preferences that affect demand for products. However, the industry classification is somewhat coarse. There are only 82 industries I can consistently measure in manufacturing. It is therefore possible that there are changes in product demand occurring within industries. To the extent these are correlated with the use of robots in production, these could be biasing my results. It seems most likely that changes in preferences and trade-induced shifts in demand would both point in the direction of favoring higher-quality products. If robots were consistently associated with products of a particular kind, it would be possible to sign the direction of this bias. Unfortunately, however, it is not clear that robots are used to automate higher or lower quality products within a given industry. There are forces pushing in both directions. For example, lower quality goods may have a higher volume, and thus increase the incentives to automate (given the fixed costs of automation). On the other hand, robots enable the creation of some products that are too difficult for humans construct manually, and these are likely to be of higher quality than the manually-produced versions (Dixon, Hong, and Wu 2019).

A third issue concerns the labor supply side. There were large changes in demographics and skills supplies over this period. It could be that educational upgrading of the workforce, for example, increased the relative supply of high skill workers and reduced it for low skill workers. I would then see this reduced supply of low-skill workers, who work in occupations most exposed to robots, and attribute the decline to reduced demand induced by automation, rather than simply reduced supply. To address these issues, I control for terciles of education in column (4) of the two regression tables. This reduces the magnitude of the coefficients by 40-50%, but they remain large and statistically significant.

Fourth, I consider the possibility that wage polarization unrelated to robot adoption may be driving my results. A large literature in economics has documented that wages for middle-skill workers have declined over the time period I study, while wages at the very top have increased.[13] To check that these are not driving my results, I control for a occupation average wage and its square in column (5) of the two regression tables. This has little impact on the results.

5 Application: Software

This section considers my second historical case study: software. Recapitulating the sequence of analyses for robots, I first briefly describe what software is and how I construct the exposure measure, before presenting the key results. I present evidence on the distributional impacts of software, and, finally, study the relationship between software exposure and changes in wages and employment.

5.1 Background and definition

Software refers to computer programs that implement manually-specified "if-then" rules. Conceptually, I regard a computer program as software (as opposed to AI) if every action it performs has been specified in advance by a human. This requires human programmers to be able to anticipate every

[13] See, for example, Michaels, Natraj, and Van Reenen (2013).

Table 6: **Top extracted verbs and characteristic nouns for software.**

Verb	Example nouns	Verb	Example nouns
record	data, position, log, location, reservation, transaction	**detect**	defect, error, malware, fault, condition, movement
store	program, data, information, image, instruction, value	**generate**	data, image, file, report, map, key, password, animation, diagram
control	access, display, unit, image, device, power, motor	**measure**	rate, performance, time, distance, thickness
reproduce	data, picture, media, file, sequence, speech, item, document, selection	**receive**	signal, data, information, message, order, request, instruction, command

Notes: This table lists the top eight verbs by pair frequency extracted from the title text of patents corresponding to software, together with characteristic direct objects for each verb chosen manually to illustrate a range of applications. Patents corresponding to each technology are selected using a keyword search. A dependency parsing algorithm is used to extract verbs and their direct objects from patent titles.

contingency, and also to be able to describe the steps required to complete the task. Examples of software include most applications we use on our computers, such as word processing, spreadsheet software, and web browsers, as well as business applications such as enterprise resource planning and reservation and ticketing systems.

5.2 Patent selection

To calculate exposure scores for software, I first define the set of patents that represent software applications. Unlike for robots, where I had to construct my own definition, there is already a standard definition of software patents in the literature. This was developed in Bessen and Hunt (2007). In that paper, the authors follow a variant of the procedure I followed for robots: they manually created a "test set" of patents that they labeled as either software or not software, identified candidate key terms, and constructed a keyword search algorithm using these terms that they then validated against their test set. Their final search algorithm require one of the keywords "software", "computer", or "program" to be present, and none of the keywords "chip", "semiconductor", "bus", "circuity", or "circuitry" to be present. This algorithm has a recall rate (fraction of "true" software patents retrieved) of 78%, and a false discovery rate of 16% on their test set.

5.3 Measurement results

Top verb-noun pairs from patents Table 6 presents the most frequent verbs and illustrative nouns extracted from the software patents. They include recording information, reservations, and locations;

Table 7: **Occupations with highest and lowest exposure to software.**

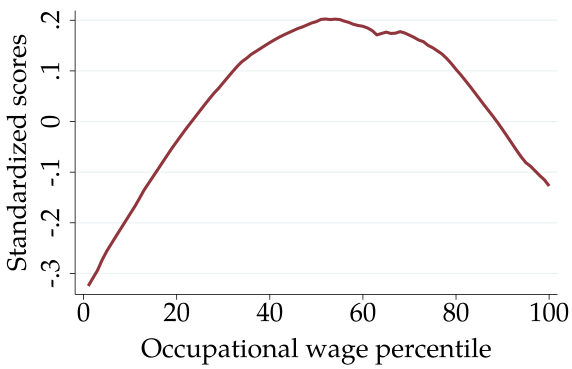
Most exposed occupations	Least exposed occupations
Broadcast equipment operators	Barbers
Water and sewage treatment plant operators	Podiatrists
Parking lot attendants	Subject instructors, college
Packers and packagers by hand	Art/entertainment performers
Locomotive operators: engineers and firemen	Mail carriers for postal service

Notes: Table displays census occupation title for the five occupations with the highest exposure scores and with the lowest exposure scores above employment threshold of 150.

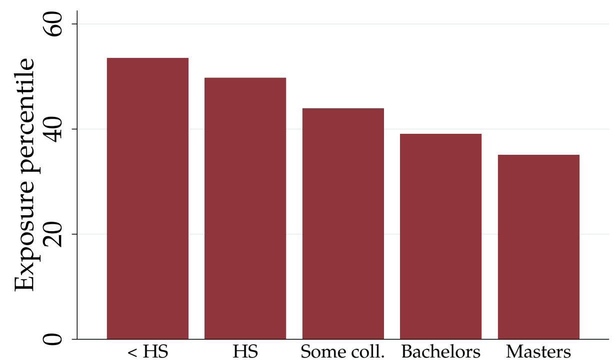
controlling access and displays; storing information, values, and instructions; reproducing media; and executing programs, logic, and rules. These activities may be summarized as manipulating information according to pre-defined rules, reflecting very closely our conceptual definition of software.

Most and least exposed occupations Table 7 presents the top 5 and bottom 5 occupations by software exposure. The most-exposed occupations include broadcast equipment operators, plant operators, parking lot attendants, and packers and packagers. These are all occupations that involve processing information according to pre-defined rules, and have all seen computers take over large parts of their tasks. For example, many parking lot attendants have been fully replaced by software-driven parking permit payment machines, which record and track information pertaining to vehicles and process payments according to pre-defined rules. Occupations least exposed to software include barbers, podiatrists, and postal service mail carriers. These are occupations that have substantial manual components that are not easy to hard-code in advance, and, in many cases, interpersonal components too.

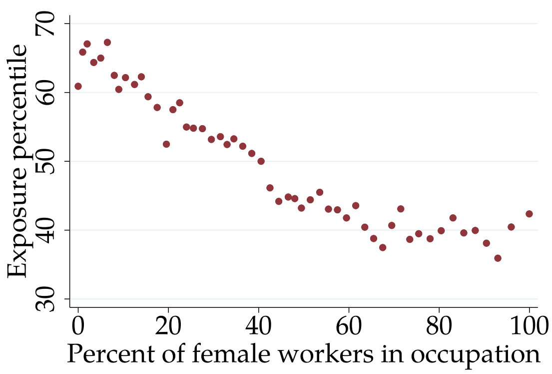
Comparison to Autor, Levy, and Murnane (2003) As a form of qualitative validation, I compare my occupation-level software exposure scores to the measures of routineness developed in Autor, Levy, and Murnane (2003). That paper's measures of routine manual and routine cognitive tasks were designed to capture the tasks for which software substitutes. I find that routine manual and routine cognitive scores are strongly positively correlated with my measures of software exposure. Full details are provided in Appendix D.1.



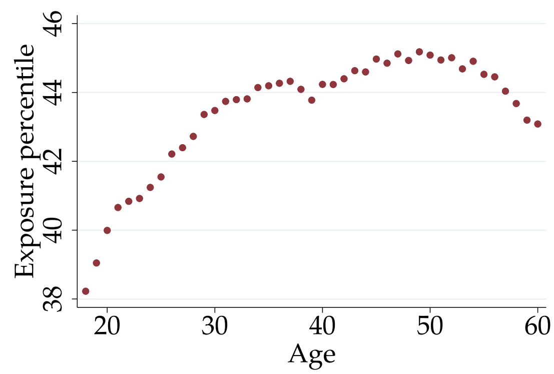
(a) Smoothed scores by occupational wage percentile



(b) Exposure by level of education



(c) Exposure by percent of female workers in occupation



(d) Exposure by age.

Figure 5: **Exposure to software by demographic group**

Notes: Plot (a) shows the average of standardized occupation-level exposure scores for software by occupational wage percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), following Acemoglu and Autor (2011). Wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean hourly wage in the May 2016 Occupational Employment Statistics. Plot (b) is a bar graph showing the exposure score percentile for software averaged across all industry-occupation observations, weighted by 2010 total employment in given educational category. Plot (c) is a binscatter. The x-axis is the percent of workers in an industry-occupation observation reported female in the 2010 census. Plot (d) is a binscatter. The x-axis is the average age of workers in an industry-occupation observation in the 2010 census.

5.4 Distributional impacts of software: descriptive evidence

To examine the distributional impacts of software, I study the kinds of people who work in occupations highly exposed to software, following the same analysis procedure as for robots. The results are presented in Figure 5. Panel (a), exposure scores by occupational wage percentile, shows that middle-wage occupations are most exposed to software. This is consistent with the literature on polarization, which has found that I.T. has reduced demand for middle-wage jobs while increasing it for low- and high-wage jobs.[14] Panel (b) presents exposure scores by individuals' levels of education. With robots, exposure was sharply decreasing with education. For software, exposure is still decreasing with education, but much less sharply.

Panel (c) plots average exposure scores against percent of female workers in occupation. This shows that occupations whose workers are predominantly male are much more exposed to software than occupations with a primarily female workforce. This might be surprising, given that much of the office work taken over by software has traditionally been performed by women. However, woman also cluster in occupations requiring complex interpersonal interaction tasks, which software is not capable of performing. Finally, panel (d) shows that software exposure is moderately increasing in age.

5.5 Relationship between exposure and changes in wages and employment

To study the relationship between occupations' exposure to software and changes in wages and employment, I follow the same empirical strategy as for robots, described in Section 4.5.1. The only difference is that whereas I restrict the sample for robots to industries in the manufacturing sector, for software, I use all industries.

Figure 6 is a residual binscatter at the occupation-industry level showing the relationship between robot exposure and changes in employment (blue line, left axis) and changes in wages (red line, right axis), after controlling for industry fixed effects. Regression results corresponding to the binscatter are presented in Tables 8 and 9. The sequence of columns is the same as for robots.

These results are quantitatively large, but not as large as for robots. For example, moving from the 25th to the 75th percentile of exposure to software is associated with a decline in within-industry employment shares of between 7 and 11%, and a decline in wages of between 2 and 6%.

These results for software face potential endogeneity from a similar set of sources to robots. Tables 8 and 9 present results controlling for offshorability, education, and wage polarization. The coefficient on exposure scores is robust to these controls in the employment regressions, with the

[14] See, for example, Michaels, Natraj, and Van Reenen (2013).

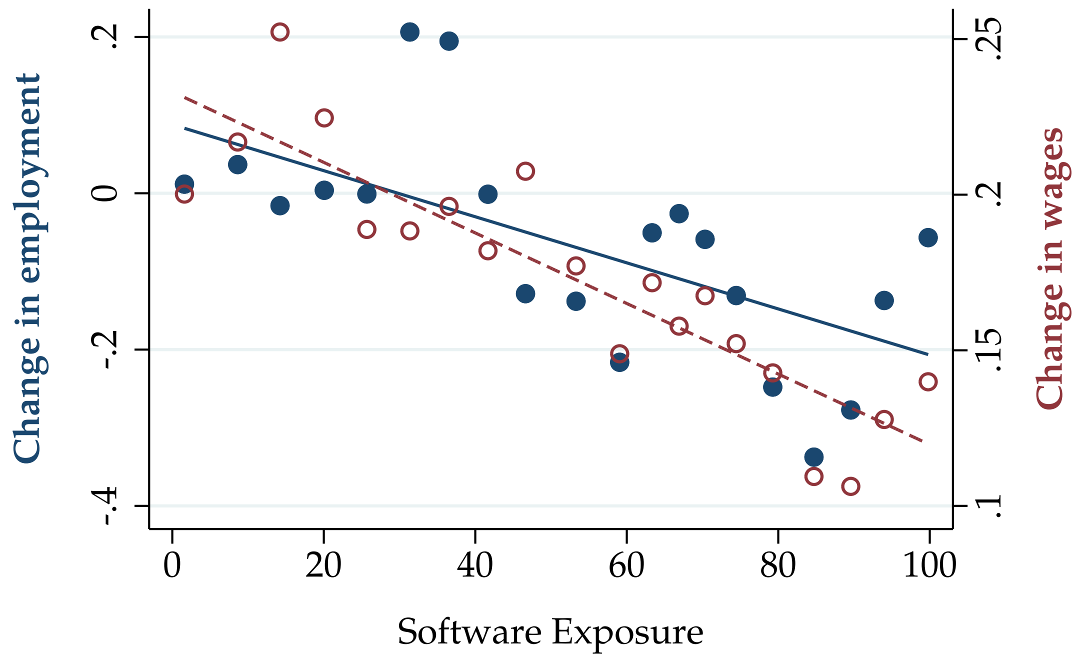


Figure 6: **Change in employment and wages 1980-2010 by exposure to software.**

Notes: Plot is a binscatter. Change in employment is measured as DHS change of an occupation-industry cell's share of overall employment between 1980 and 2010, winsorized at the top and bottom 1%. Change in wages is measured as log difference in a cell's mean FTFY weekly wage. Controls added for industry fixed effects.

Table 8: **Change in wages vs. exposure to software, 1980-2010.**

	(1)	(2)	(3)	(4)	(5)
Exposure	-0.13***	-0.11***	-0.09***	-0.05***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Offshorability			2.02***	1.42***	-0.87***
			(0.30)	(0.29)	(0.28)
Medium education				8.36***	11.80***
				(0.99)	(0.93)
High education				12.77***	32.75***
				(1.07)	(1.24)
Wage					-0.07***
					(0.00)
Wage squared					0.00***
					(0.00)
Adjusted R^2	0.008	0.064	0.067	0.079	0.168
Industry FEs		✓	✓	✓	✓
Observations	18,975	18,975	18,975	18,975	18,975

Notes: Each observation is an occupation-industry cell. Dependent variable is 100x change in log wage between 1980 and 2010 winsorized at the top and bottom 1%. Observations are weighted by cell's labor supply, averaged between 1980 and 2010. Education variables are terciles of average years of education for occupation-industry cells in 1980. Wages are cells' mean weekly wage for full-time, full-year workers in 1980. Offshorability is an occupation-level measure from Autor and Dorn (2013). Standard errors are clustered by industry. * p<0.10, ** p<0.05, *** p<0.01.

wage regressions being somewhat more sensitive. While these results clearly do not isolate the causal effect of exposure to software on occupations, the overall pattern of results suggests that exposure to software has resulted in declines in employment and wages for affected occupations over the past several decades.

6 Application: AI

In the previous two sections, I explored two historical case studies, software and robots. In this section, I apply the method to artificial intelligence. The section has three parts. First, I outline a conceptual framework that characterizes the kinds of tasks AI can perform. The framework serves

Table 9: **Change in employment vs. exposure to software, 1980-2010.**

	(1)	(2)	(3)	(4)	(5)
Exposure	-0.30***	-0.22***	-0.21***	-0.14***	-0.14***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Offshorability			2.98***	2.07***	2.66***
			(0.51)	(0.52)	(0.53)
Medium education				7.28***	6.19***
				(1.33)	(1.35)
High education				27.47***	22.26***
				(1.83)	(1.91)
Wage					0.03***
					(0.00)
Wage squared					-0.00***
					(0.00)
Adjusted R^2	0.009	0.193	0.194	0.207	0.210
Industry FEs		✓	✓	✓	✓
Observations	36,070	36,070	36,070	36,070	36,070

Notes: Each observation is an occupation-industry cell. Dependent variable is 100x DHS change of a cell's share of overall employment between 1980 and 2010, winsorized at the top and bottom 1%. Education variables are terciles of average years of education for occupation-industry cells in 1980. Wages are cells' mean weekly wage for full-time, full-year workers in 1980. Offshorability is an occupation-level measure from Autor and Dorn (2013). Observations are weighted by cell's labor supply, averaged between 1980 and 2010. Standard errors are clustered by industry. * p<0.10, ** p<0.05, *** p<0.01.

as a lens through which to interpret the results of the empirical analysis. Second, I apply my method to artificial intelligence patents, and present results that are purely descriptive. Finally, I make some strong assumptions in order to predict the impacts of artificial intelligence on wage inequality. The results in this final section are necessarily more speculative, and are independent of the rest of the analysis. The key takeaway from this section is that artificial intelligence is qualitatively different from software and robots. This difference means that it will affect different kinds of jobs, and so likely have different effects on labor demand, than these previous technologies.

6.1 Definitions and conceptual framework

In this subsection, I first define artificial intelligence, then use this definition to elaborate a conceptual framework that characterizes the kinds of tasks that artificial intelligence can perform. I developed this framework through more than 50 interviews with computer scientists at the forefront of AI research.

Definitions I use the term artificial intelligence to refer to machine learning algorithms. Specifically, I have in mind two kinds of machine learning algorithms: supervised learning and reinforcement learning algorithms. I define these further below. I recognize that artificial intelligence has broader scope, and my use is not meant prescriptively. My focus is motivated by the dramatic practical advances in supervised and reinforcement learning in recent years (Krizhevsky, Sutskever, and Hinton 2012; Mnih et al. 2015) and their broad economic applicability.

The definition of supervised learning is as follows. A supervised learning algorithm learns functions that map inputs into outputs from training data consisting of example input-output pairs. One of the simplest examples of a supervised learning algorithm is linear regression. With linear regression, the inputs are the independent variables, and the output is the dependent variable. Supervised learning extends beyond the standard uses of linear regression in economics along two dimensions. First, it allows for a much more flexible relationship between the inputs and the outputs. Second, inputs and outputs may be any kind of data, such as text or images. For instance, a supervised learning algorithm may learn a function that maps an image (input) into a textual description of the image (output), using a bank of examples of image-description pairs. With appropriate training data, it could learn to map a customer's financial history into their likelihood of repaying a loan, or sentences in one language into another. The algorithm learns the statistical relationships present in the training data, so, in a loose sense, the data must "contain" enough information for it to learn the function.

A reinforcement learning algorithm, by contrast, learns how to take actions in a dynamic environment in order to achieve an objective. This sounds like the definition of optimal control, and, indeed, dynamic programming is an example of a reinforcement learning algorithm. However, whereas dynamic programming is typically used with environments that have a very low-dimensional state space, recent research in reinforcement learning has enabled the application of similar principles to more complex settings, such as three-dimensional physical environments. Examples might be controlling the fingers of a robot hand to perform dextrous manipulation, operating the machinery in a factory to optimize energy efficiency, or exchanging messages with a human to troubleshoot a technical problem. These algorithms learn by a kind of trial-and-error, so, in order to succeed, they require experiments in the environment, or a good simulator of it, and a way of evaluating performance.

Conceptual framework These requirements suggest three constraints on the kinds of tasks that can be performed by artificial intelligence algorithms. First, there must be enough of the right kind of training data available. Second, the task must have an objective that is easy to measure. Third, the algorithm must have access to the "levers" it needs to complete the task. I now describe each constraint in more detail, and give examples of tasks that do and do not satisfy each one.

First, consider data availability. This is important for both supervised and reinforcement learning, but in different ways. In supervised learning, there must be enough examples of the task being done correctly for the algorithm to learn from. Certain kinds of information are regularly stored at scale, like system logs, sensor data, and records kept by humans. Some tasks, such as operating a power plant or auditing a company's accounts, involve processing such information and little else. This makes them a good target for supervised learning. Other tasks, like discussing a treatment plan with a patient or advising a student on their research, consist of interactions that are not usually recorded, perhaps because doing so would be unethical or illegal. This makes training data difficult to obtain. Data must also be sufficiently comprehensive. A company may have enough recordings of customer support interactions to train an algorithm to answer queries about its current products. But as soon as it releases a new product, new training data will be required. In general, tasks with stable, systematic relationships between inputs and decisions, such as sorting agricultural products, translating languages, or interpreting medical images, are much easier to learn than tasks with frequent changes or one-off exceptions, such as those handled by customer service supervisors, flight attendants, or any kind of team leader.

In reinforcement learning, learning by trial-and-error takes the place of learning from examples. Experimentation by an algorithm in the real world can be costly or unethical, so learning in simulation is often preferred (Rusu et al. 2016). A simulator may itself be learned from observational data, again requiring that such data be available (Rezende, Mohamed, and Wierstra 2014). Alternatively, a human could build a simulator manually. This may be possible for human-designed systems, like robots or industrial processes, and for well-understood aspects of the natural world, like classical mechanics. But manually building a simulator of a human to interact with would be more difficult. This means that, in practice, robotic locomotion and dextrous manipulation are more amenable to reinforcement learning than, say, motivational speaking, product development, or public relations. For the same reason, physical activities in contexts like assembly lines that are strictly regimented, hence easy to simulate, are easier to learn than physical activities in more variable contexts like construction sites, homes, or offices.

The second constraint on the kinds of tasks amenable to artificial intelligence is that they must have an objective that is easy to measure. This is because algorithms need to evaluate their performance in order to improve. Optimizing for energy efficiency is possible because energy efficiency is easily measurable. But it is less easy to measure success in tasks like writing a corporate strategy, negotiating an agreement, leading a team, or even tidying a room, and optimizing a misspecified objective can be highly counterproductive (Amodei et al. 2016). Delayed feedback, which characterizes many activities, makes learning even harder (Sutton 1984). An algorithm could ask for guidance from a human (Christiano et al. 2017), but a human may not have the patience to give it, especially if they are a paying customer. Most algorithms also need too many examples to be able to learn from a single human in real time. Tasks with objectives that can be evaluated immediately and automatically, such as maximizing the click-through rate of an ad, or minimizing the materials costs of a computer chip, are thus easier for algorithms to learn than tasks with "fuzzier" or longer-term objectives, such as many managerial activities.

The final constraint is the action space, or "levers", available to the algorithm. Most humans can walk and speak, many can sign contracts, and some can get the president on the phone. Algorithms, by contrast, run on silicon chips. They interact with the world only by issuing electronic commands to other systems via human-constructed interfaces. These interfaces may be costly to create, such as when physical equipment or legacy software systems are involved (David 1990). Prudence or regulation may limit interfaces that pose safety, operational, financial, or other kinds of risk. And many activities, such as those of investigative journalists, executive recruiters, or managers, depend on human relationships, which are hard for algorithms to acquire. All these severely limit the kinds of tasks amenable to automation of any kind, including artificial intelligence.

Relationship of artificial intelligence to robots and software How does artificial intelligence differ from software? With artificial intelligence, the human programmer defines the learning algorithm, which then learns for itself from data or experimentation how to achieve an objective. With software, as noted above, the human programmer must code a sequence of "if-then" steps that directly completes the task (Autor, Levy, and Murnane 2002). Many applications, such as algorithms for self-driving cars, involve a mixture of both, so the distinction is not always clean. In the labor economics literature, tasks whose execution steps can be expressed as a codified sequence of instructions by a programmer have been labeled "routine" (Autor, Levy, and Murnane 2003). Tasks for which it is impractical to write down the execution steps are known as "non-routine". Software can therefore carry out routine tasks, in this sense, but not non-routine ones. In principle, artificial intelligence is not limited to routine tasks, and, indeed, I find using my method that many non-routine tasks are highly exposed to artificial intelligence.

What about robots? Robots are physical pieces of equipment. To do anything useful, such a piece of equipment must be given instructions. Historically, these instructions have been provided by software. This means that each robot action must be specified in advance. Variability in the physical environment, and in the task itself, must therefore be kept to a minimum, since any change necessities an expensive re-programming of the robot. Moreover, many useful tasks, such as picking up arbitrary objects in a warehouse, are so variable by definition that it is impossible to program them using software. This picture changes with artificial intelligence. Within the constraints described in the previous section, an algorithm can learn for itself how to map information about the environment, such as visual and tactile data from the robot's sensors, into instructions sent to the robot's actuators. This means that many tasks it was impossible to program robots to do using traditional software methods may now become possible using artificial intelligence.

6.2 Patent selection and descriptives

To select artificial intelligence patents, I use search terms corresponding to the definition presented above. The terms are "supervised learning" and "reinforcement learning", together with "neural network" and "deep learning". Neural networks are the general-purpose function approximators used in both supervised and reinforcement learning, and "deep" neural networks have been a key driver of the recent success in applications. The use of deep neural networks in machine learning is often described as "deep learning".

6.3 Measurement results

Table 10 presents the most frequent verbs and illustrative nouns extracted from artificial intelligence patents. They include recognizing speech and voices, predicting prognosis and treatment, recognizing images and detecting cancel, identifying damage, and detecting fraud. These are tasks involved in, for example, medical imaging and treatment, insurance adjusting, and fraud analysis, all areas that are currently seeing high levels of AI research and development. Notably, these activities are of a very different kind to those identified for robots and software. Whereas robots perform "muscle" tasks and software performs routine information processing, AI performs tasks that involve detecting patterns, making judgments, and optimization.

The fact that AI performs different tasks from robots and software suggests that it is likely to affect different occupations. Indeed, I find that the set of occupations exposed to AI is very different to that exposed to robots and software. The most and least exposed occupations are

Table 10: **Top extracted verbs and characteristic nouns for AI.**

Verb	Example nouns	Verb	Example nouns
recognize	pattern, image, speech, face, voice, automobile, emotion, gesture, disease	**determine**	state, similarity, relevance, importance, characteristic, strategy, risk
predict	quality, performance, fault, behavior, traffic, prognosis	**control**	process, emission, traffic, engine, robot, turbine, plant
detect	signal, abnormality, defect, object, fraud, event, spammer, human, cancer	**generate**	image, rating, lexicon, warning, description, recommendation
identify	object, type, damage, illegality, classification, relationship, importance	**classify**	data, object, image, pattern, signal, text, electrogram, speech, motion

Notes: This table lists the top eight verbs by pair frequency extracted from the title text of patents corresponding to AI, together with characteristic direct objects for each verb chosen manually to illustrate a range of applications. Patents corresponding to each technology are selected using a keyword search. A dependency parsing algorithm is used to extract verbs and their direct objects from patent titles.

displayed in Table 11. Consider some of the occupations most exposed to AI. Clinical laboratory technicians perform the visual and analytical work of identifying pathologies from medical tests; AI applications have now been developed to automate much of this work (Janowczyk and Madabhushi 2016). Chemical engineers design and operate chemical production processes. AI algorithms are particularly well-suited to these discovery and optimization tasks, and are already being used in such applications (Agrawal, McHale, and Oettl 2019; Goh, Hodas, and Vishnu 2017). Optometrists detect diseases in the eye. Optometry is the area of medicine that has seen perhaps the most success of AI algorithms to date (De Fauw et al. 2018). Finally, power plant operators control all kinds of equipment to generate the right amount of power in a safe and energy efficient manner. To date, several companies who run power plants and data centers have replaced manual human operation with AI algorithms, which are able to achieve much more efficient operation than human engineers (Lazic et al. 2018).

While these are all high-skilled jobs, it is worth noting that there are also low-skilled jobs that are highly exposed to AI. For example, many production jobs that involve inspection and quality control are exposed to AI. However, as we will see in the next section, these jobs constitute a small proportion of the low-skill workforce, meaning that low-skilled jobs are less exposed to AI on an employment-weighted basis.

The occupations least exposed to AI include college professors, food preparation workers, and postal service mail carriers. We can loosely split these occupations into three categories. First, there

Table 11: **Occupations with highest and lowest exposure to artificial intelligence.**

Most exposed occupations	Least exposed occupations
Clinical laboratory technicians	Animal caretakers, except farm
Chemical engineers	Food preparation workers
Optometrists	Mail carriers for postal service
Power plant operators	Subject instructors, college
Dispatchers	Art/entertainment performers

Notes: Table displays census occupation title for the five occupations with the highest exposure scores and with the lowest exposure scores above employment threshold of 150.

are high-skill occupations that involve reasoning about situations that have never been seen before, such as various kinds of researcher. Second, there are occupations of all skill levels that involve interpersonal skill, such as teachers and managers. Third, there is manual work that occurs in non-factory environments, and that often involves some element of interpersonal skill too, such as baristas, food preparation workers, or massage therapists.

6.3.1 Industry case studies

To draw out these differences, it is instructive to consider sets of superficially similar occupations in the same industry. First, consider legal occupations. The large number of companies working on artificial intelligence for the law makes it tempting to conclude that lawyers will soon be made obsolete. However, my results suggest that two other occupations, paralegals and administrative law judges, are much more exposed to AI than lawyers themselves. The reason for this is clear from their tasks. Paralegals spend most of their time reviewing documents. These tasks, such as reviewing contracts for unusual clauses, are highly amenable to automation using AI. This is because the objectives can be clearly specified (e.g., "score this clause for how common it is in contracts of this type"), and there exist large amounts of relevant training data, often in the public domain. Administrative law judges, similarly, spend most of their time making judgments on cases that are highly standardized and for which the law is settled. By contrast, lawyers spend much of their time conferring with clients and colleagues, representing clients in negotiations and court cases, and working on cases for which sufficient precedent does not exist for an algorithm to be trained successfully. This mix of interpersonal work and handling novel situations renders them only very lightly exposed to AI. This conclusion matches other work that has considered this question. Remus and Levy (2017) conduct a careful manual study of laywers' time use, based on data from a legal billing software vendor. For each category of activity, they identify the amount of the activity it is possible to automate, based on a detailed examination of the technical details and currently available commercial products. They, too, find that the vast majority of lawers' time is spent on activities that are not amenable to artificial intelligence.

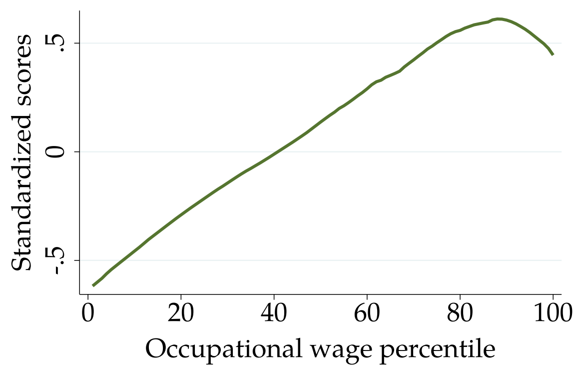
Second, consider healthcare occupations. Again, the high degree of media attention devoted to the use of artificial intelligence in certain healthcare tasks, such as diagnosis, makes it easy to assume that doctors will be most impacted by artificial intelligence. My exposure scores for healthcare occupations suggest that this is an incomplete picture. Doctors do have some exposure to AI, given their task of diagnosing conditions, which is highly exposed. However, their work contains substantial interpersonal components, meaning they are only lightly exposed overall. Nurses are similar: some parts of their jobs, such as monitoring patients for changes in condition, are highly exposed to AI, while other parts, such as talking to patients, preparing them for treatments, and coordinating with healthcare team members, are not. By contrast, some more specialized medical occupations are highly exposed. Medical technicians, optometrists, and pathologists all specialize in precisely the things that AI automates, meaning they are highly exposed. Lower-skill healthcare occupations, such as home health care aides, are much less exposed, given highly variable physical and interpersonal activities they perform.

6.4 Distributional impacts: descriptive evidence

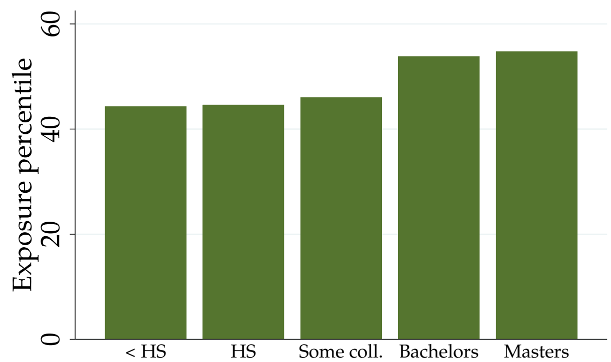
I now turn to the distributional impacts of artificial intelligence. First, I present purely descriptive evidence on the kinds of people who work in occupations that are exposed to artificial intelligence. In the next section, I make some strong additional assumptions in order to make predictions about employment and wage impacts.

Figure 7 presents distributional results as for robots and software. Panel (a) plots exposure scores against occupational wage percentiles, with percentiles weighted by hours worked. This figure shows that low-wage occupations are least exposed, and high-wage occupations much more exposed. Together, these two panels reflect the fact that the things AI is good at — activities involving detecting patterns, judgment, and optimization — tend to be performed by higher-skill workers. As noted above, there are low-skilled jobs that are highly exposed to AI, such as production jobs involving inspection and quality control. However, these jobs constitute a small proportion of the low-skill workforce. Low-skilled people today are much more likely to work in face-to-face service occupations, such as in retail and food service, that are less exposed to AI. Panel (b) presents exposure scores by individuals' levels of education. AI has the opposite pattern to robots and software: exposure is increasing in education, with those with master's degrees most exposed.

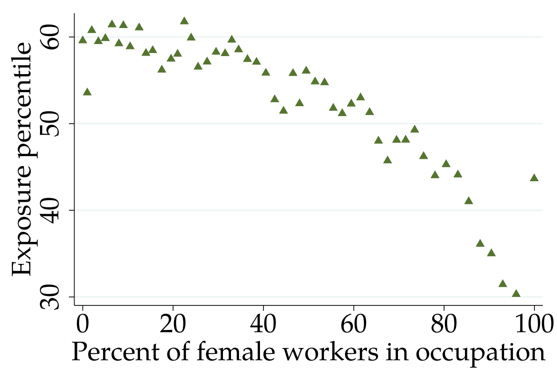
Panel (c) plots average exposure scores against percent of female workers in occupation. In this



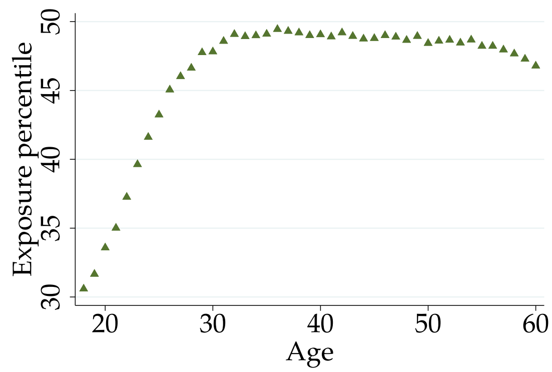
(a) Smoothed scores by occupational wage percentile



(b) Exposure by level of education



(c) Exposure by percent of female workers in occupation



(d) Exposure by age.

Figure 7: **Exposure to AI by demographic group**

Notes: Plot (a) shows the average of standardized occupation-level exposure scores for AI by occupational wage percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), following Acemoglu and Autor (2011). Wage percentiles are measured as the employment-weighted percentile rank of an occupation's mean hourly wage in the May 2016 Occupational Employment Statistics. Plot (b) is a bar graph showing the exposure score percentile for AI averaged across all industry-occupation observations, weighted by 2010 total employment in given educational category. Plot (c) is a binscatter. The x-axis is the percent of workers in an industry-occupation observation reported female in the 2010 census. Plot (d) is a binscatter. The x-axis is the average age of workers in an industry-occupation observation in the 2010 census.

respect, AI looks much more the other technologies, with "male" jobs much more exposed to AI than "female" ones. This reflects the fact that men have historically been much more likely than women to work in the technical jobs exposed to AI, while, again, women have been more likely to work in roles requiring more interpersonal skill, which are less exposed to AI.

Finally, Panel (d) shows the results by individuals' age. As might be expected from the fact that AI-exposed jobs are predominantly those involving high levels of education, judgment, and therefore accumulated experience, it is older workers who are most exposed to AI. Younger workers are barely exposed at all. This means that AI potentially represents a "triple wammy" for older workers. First, older workers tend to be less mobile than younger workers, in terms of both occupation and geography, making it more difficult for them to adapt. They also have fewer years of working life remaining, making educational and training investments less attractive for them. Second, there are increasingly many of them, due to the aging of the Baby Boomer generation. So the supply of this demographic is substantially increasing. These first two issues would be potentially negative for any automation technology. The third issue is that AI, in particular, is predicted to impact precisely the occupations that older workers predominantly work in. If the impacts of exposure to AI are negative, these negative impacts may therefore be more concentrated on older workers than the impacts of software and robots. On the other hand, there is some evidence that most changes in employment by occupation occur via the entry margin, that is, fewer young workers joining the occupation, than via the exit margin, that is, more older workers leaving it (voluntarily or involuntarily) (Webb and Chandler 2018). As such, the impacts on individuals are likely to be more nuanced than a simple calculation of exposure by demographic would suggest.

6.5 Potential impacts on inequality

This section moves from purely descriptive results about the occupations and groups exposed to AI to a quantification of its potential impacts on inequality. To do this, I make the additional assumption that the relationship between AI exposure and changes in wages will have the same negative, approximately linear relationship as the relationship that existed between exposure to software and robots and changes in wages. There are, of course, reasons why this may not be the case, which I explore below. The results in this section simply extrapolate directly from the patterns identified in the historical case studies, and explore the consequences for inequality given the very different occupations that are exposed to AI compared to robots and software.

Under the assumption of a linear, negative relationship between AI exposure and changes in wages, I calculate the wage distribution for different potential magnitudes of this relationship. I take the average wage for every occupation in 2010, and adjust each one by its AI exposure score

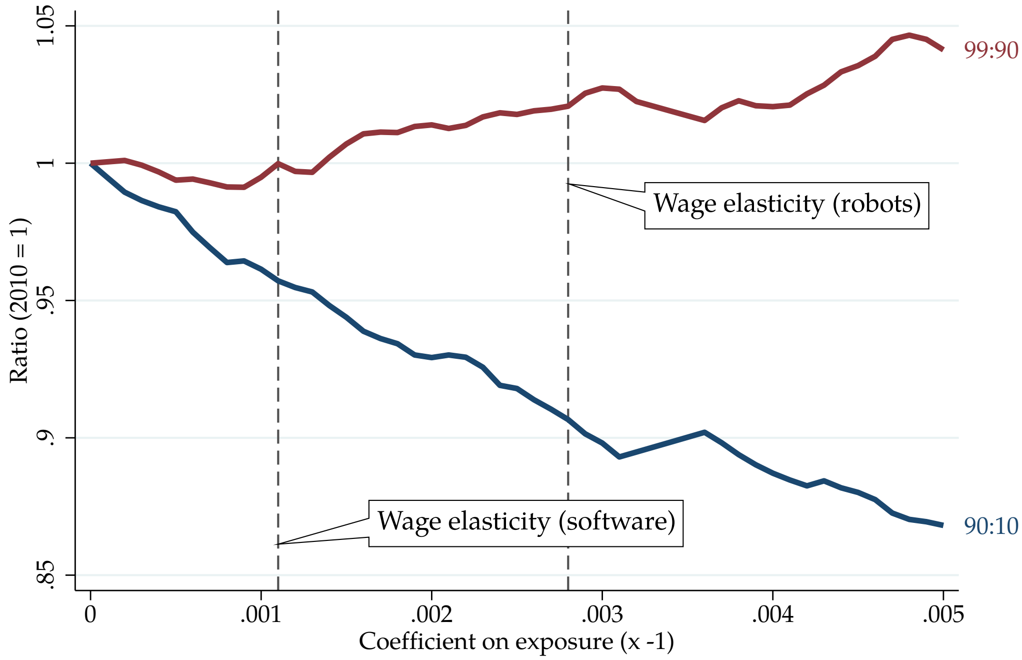


Figure 8: **Potential impacts of artificial intelligence on inequality.**

Notes: Ratios calculated from the percentiles of wage $* \, e^{\beta * \text{exposure}}$ for various values of β, the coefficient on exposure in a regression with change in log wages as the dependent variable. The sign of the coefficient has been flipped.

multiplied by a sequence of coefficient values ranging from 0 to 0.005. This range reflects the range of coefficient estimates on exposure scores that I estimate in the wage regressions for robots and software. In those regressions, the dependent variable was the change in log wages between 1980 and 2010. This range therefore represents impacts that took several decades to occur for software and robots. For each value of the coefficient, I re-calculate the percentiles of the distribution of average wages across occupations. I then calculate the ratios of the 90th to the 10th percentile of wages, and the ratio of the 99th to the 90th percentile.

Figure 8 plots these ratios as a function of the magnitude of the exposure coefficient. A marginal increase in the exposure coefficient, which corresponds to a greater impact of AI, is associated with a marginal decline in the 90:10 ratio, but a marginal increase in the 99:90 ratio. A coefficient on exposure equivalent to that estimated for software is associated with a 4% decrease in 90:10 inequality; using the coefficient estimated for robots, the decrease is 9%. In other words, AI could compress wages in the middle of the distribution, but expand inequality at the top. The pattern for the 90:10 ratio reflects the fact that high-wage occupations are relatively more exposed to AI than low-wage occupations. The pattern for the 99:90 ratio reflects the fact that the very highest-paid occupations, such as CEOs and professionals, are less exposed.

6.6 Discussion

These results should be interpreted with caution. First, they rely on a constant mapping between my exposure scores and changes in demand. In the language of the model, they require that the structural parameters of the elasticities of substitution at various levels remain constant. This does not seem unreasonable, but it is certainly a strong assumption. The fact that the relationship between exposure scores and changes in wages was negative for both historical case studies shows that the balance of forces favored substitution in the past. This may move our priors toward thinking that the same will be true in the future. To the extent this relationship no longer holds, however, these projected impacts will be invalid.

Second, when considering the impacts on inequality, a number of measurement issues arise. For example, there have been substantial changes in the way that top earners receive their income in recent decades (Smith et al. 2019), and these are not captured in my exercise. I also do not capture the fact that owners of capital may benefit from artificial intelligence (Freeman 2015). As such, it is likely that I am understating the increase in 99/90 inequality that may result from AI.

Third, I cannot rule out that AI will produce purely labor-augmenting technical change that will advantage some types of labor over others. As noted in the model section, however, for this to affect my results, the distribution of impacts on labor demand due to labor-augmenting technical change would need to be correlated with the distribution of impacts due to substitution. The same goes for the other ways in which technology affects labor demand, such as product rather than task-level substitution. There is no a priori reason to think this would be the case, though this is an important direction for further research.

Finally, there is the question of timing. While there is some relationship between the time pattern of patenting and that of technology adoption, we are too early in the development of AI to know how much more of the technology there is to be developed, and too early also to know how long it will take to be adopted. If history is a guide, the main impacts on the labor market may not appear for three decades (Jovanovic and Rousseau 2005; Yates 2005). AI could be faster to diffuse than previous technologies, given the lack of a need to manually specify its rules of operation. However, it could also be slower, given its vast data requirements and the need for other complementary investments (Brynjolfsson, Rock, and Syverson 2018).

7 Conclusion

This paper has developed a new method for identifying the exposure of occupations to different technologies, and applied it to two historical case studies, software and robots, and to artificial intelligence. The results leave little room for doubt that artificial intelligence is likely to affect very different kinds of occupations, and so different kinds of workers, than software and robots. Whereas low-skill occupations are most exposed to robots, and middle-skill occupations are most exposed to software, it is high-skill occupations that are most exposed to artificial intelligence. Moreover, artificial intelligence is much more likely to affect highly-educated and older workers than these previous technologies.

Substantial uncertainty about the impacts of artificial intelligence remains. While the method developed in this paper captures the tasks for which AI substitutes, it is possible that AI will also complement some kinds of tasks, with different effects on labor demand. Moreover, the impacts on workers depend not just on labor demand, the focus of this paper, but also on labor supply. In particular, future patterns of human capital investment and occupational mobility will have important effects on equilibrium employment and wages. Artificial intelligence may also affect the labor market through more indirect channels. For example, it may lead to the creation of new products, which could affect labor demand, and to more efficient delivery of education, which could affect labor supply. For all these reasons, the results presented in this paper should be seen only as a first step towards estimating the labor market impacts of artificial intelligence.

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A How to access this paper's data

This paper's data are available at the following URL: http://www.michaelwebb.co.

B Data appendix

US Census My primary source of data is population survey data extracted from U.S. census records and the American Community Survey 2010 sample in the Integrated Public Use Microdata Series (IPUMS USA). The sample is restricted to those age 18-65 who worked in the previous year.

I clean the IPUMS data using code modified from the replication files of Acemoglu and Autor (2011). The weighting variable throughout is the "labor-supply weight", obtained by multiplying the IPUMS survey person weight (PERWT) by fraction of full-time work for each observation. The total labor-supply weight value of an industry-occupation observation is thus the number of full-time-equivalent (FTE) employees in that industry-occupation cell.

I additionally create a "demographic-controlled" labor-supply weight value in order to account for changes in demographics since 1980. I first identify demographic cells by sex, race (black, white, other), education category (did not complete high school, completed high school, some college, four-year college degree), and age category (using 5-year buckets). The demographic-controlled weight for 2010 is then calculated by fixing the relative weight of each cell at 1980 levels, i.e., multiplying each observation by the ratio of that cell's total 1980 weight to the cell's total 2010 weight.

To construct the wage variables, I calculate real (2016 dollars) weekly wages in 1980 and 2010 for full-time-full-year (FTFY, more than 35 hrs/week and 40 wks/year) workers, 98% winsorized on full earnings sample by year. I collapse the census data into industry-occupation-year observations using the ind1990 and occ1990dd classifications.

The education control variable I use in my regressions is the labor-supply-weighted tercile of average years of education for industry-occupation cells in 1980.

Offshorability and RTI measures Offshorability is an occupation-level measure of the potential for an occupation to be offshored. Note that this does not measure the extent to which offshoring has actually occurred. The measure is an aggregation of several variables from the O*NET database. It "captures the degree to which an occupation requires either direct interpersonal interaction or proximity to a specific work location" (Autor and Dorn 2013).

The RTI (Routine Task Intensity) index, developed by Autor and Dorn (2013), is a measure of the routineness of an occupation. It is designed to capture potential for automation. To build the RTI score, occupations are given routine, abstract, and manual task content scores according to their job task requirements from the the US Department of Labor's 1977 Dictionary of Occupational Titles. The RTI index is then the log difference of routine task content with abstract and manual task content.

Occupational licensing data Occupations are licensed at the state level, so an occupation licensed in one state may not be licensed in other states. Additionally, the licensing requirements for many occupations have changed in the period 1980-2010, which is the period of interest for my software and robot case studies. I thus use Kleiner and Xu (2017)'s list of 45 "universally licensed" occupations: occupations licensed in every state from the 1980s to 2016. I then match this list to 47 occupations in the occ1990dd classification. Five of these occ1990dd occupations are aggregations of universally licensed occupations and non-universally licensed occupations, and are given a licensing score of 0.5. The remaining 42 universally licensed occ1990dd occupations are given a licensing score of 1; all other occupations are given a licensing score of 0.

C Supplementary exposure score figures

Table A1: **Extracting capabilities from patent titles.**

Text	**Extracted pairs**
Adaptive system and method for predicting response times in a service environment	(predict, time)
Method of and apparatus for determining optimum delivery route for articles	(determine, route)
Methods and apparatus for reinforcement learning	
Device for forecasting total power demand	(forecast, demand)
Method and device for classifying images on basis of convolutional neural network	(classify, image)
A method for diagnosing food allergy	(diagnose, allergy)
Neural network language model training method and device and voice recognition method	
Automatic butterfly species identification system and method, and portable terminal having automatic butterfly species identification function using the same	(have, function), (use, same)

Notes: Table displays a set of titles of artificial intelligence patents and corresponding verb-object pairs extracted automatically using a dependency parsing algorithm, as described in the main text. Stop words such as "use" and "have", which do not express applications, are dropped from subsequent analysis.

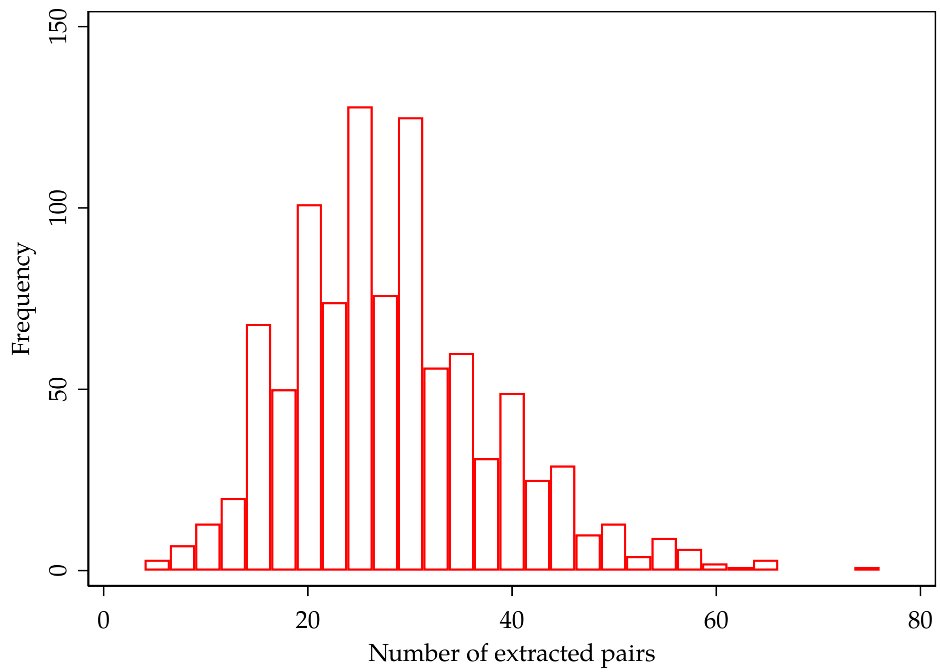

Figure A1: **Distribution of pair counts across occupations.**

Notes: Figure displays the distribution across occupations of the number of pairs extracted from an occupation's tasks in the O*NET database.

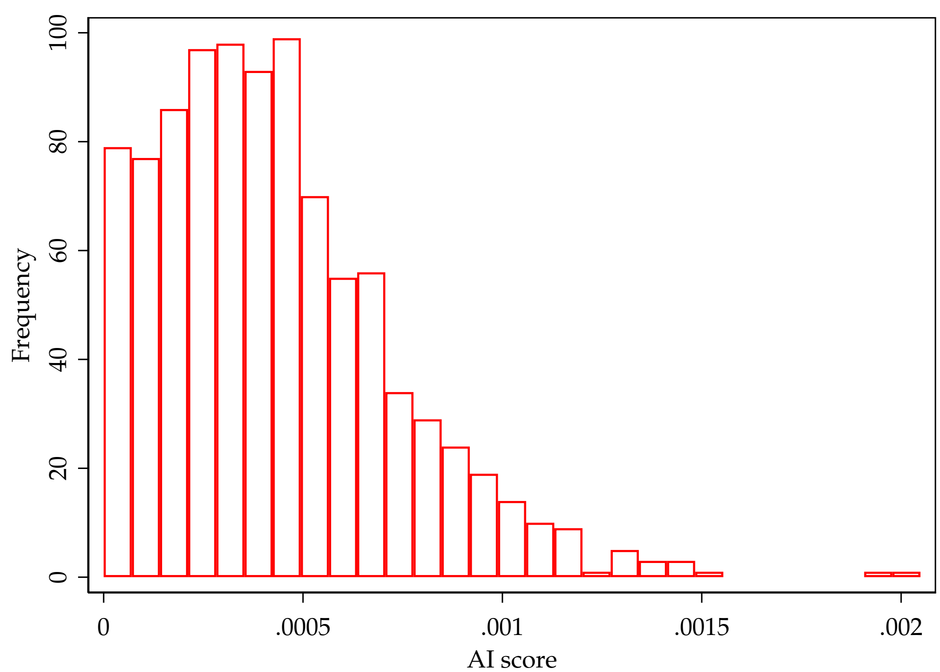

Figure A2: **Distribution of AI exposure scores across occupations.**

Notes: Figure displays the distribution across occupations of artificial intelligence exposure scores.

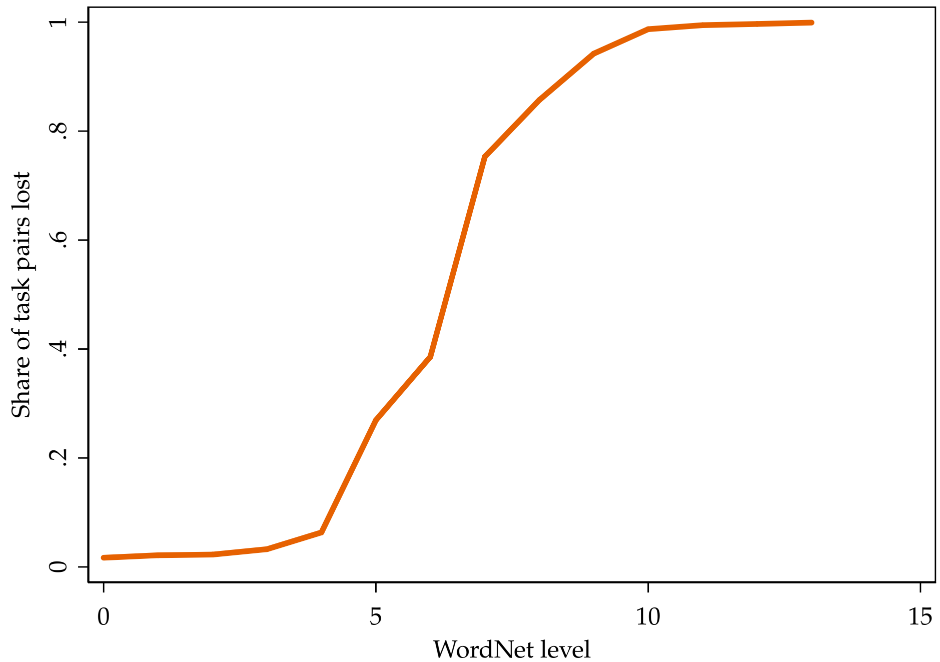

Figure A3: **Share of task pairs lost by WordNet aggregation level.**

Notes: WordNet assigns all nouns to positions in a conceptual hierarchy. For example, the ancestors of "dog" include "carnivore", "mammal", "vertebrate", "animal", and "physical entity". I group together nouns in the same conceptual category, for a given WordNet level. If I aggregated at the level of "dog", I would lose all words that exist only at a more general level, such as "mammal" and "animal". This figure displays the share of verb-noun pairs extracted from O*NET tasks that would be lost for this reason at each level of aggregation. (Levels with higher numbers are more specific.)

D Comparison of exposure scores to routineness measures

To study the relationship between my approach and the influential "routineness" approach, I regress my exposure scores for each technology on the five occupation routineness measures developed in Autor, Levy, and Murnane (2003) and Acemoglu and Autor (2011). These routineness measures are hand-crafted composites of job characteristic scores provided in O*NET; for example, the "routine cognitive" measure combines O*NET scores for how structured an occupation's work is and the importance of "repeating the same tasks". Further details on the construction of these measures are provided in Appendix D.2.

The results are plotted in Figure A4. The coefficient on the non-routine cognitive analytic measure is exceptionally high for artificial intelligence and much lower for software, suggesting that artificial intelligence has a set of non-routine capabilities that fundamentally distinguish it from software. The coefficients on the interpersonal measure are low for all three technologies, suggesting that, for now, interpersonal tasks will be harder to automate than other activities. The high non-routine manual scores reflect the fact that this score captures controlling equipment, which is a capability to some extent of all three technologies.

D.1 Comparison to Autor, Levy, and Murnane (2003)

As a further comparison exercise, I directly assess my software exposure scores against the findings in Autor, Levy, and Murnane (2003). I find that my method independently recovers that paper's key qualitative results.

In that paper, the authors argue that software should substitute for routine cognitive and routine manual tasks, and complement non-routine cognitive tasks. To test these theoretical predictions empirically, the authors study how the change in computer use in an industry is related to the change in the mix of jobs in that industry over various time periods. Specifically, in Table III they regress the average routine cognitive score of jobs in an industry, for various time periods, on change in computer use in that industry. They do the same for routine manual scores, non-routine cognitive analytic scores, and non-routine cognitive interpersonal scores. They exclude non-routine manual scores from their analysis.

They find that increased computer use is associated with rises in an industry's use of non-routine cognitive analytic occupations, larger rises in use of non-routine cognitive interactive occupations, falls in use of routine cognitive occupations, and even larger falls in use of routine manual occupations.

Figure A5 shows the results of four regressions based on the measure of exposure to software

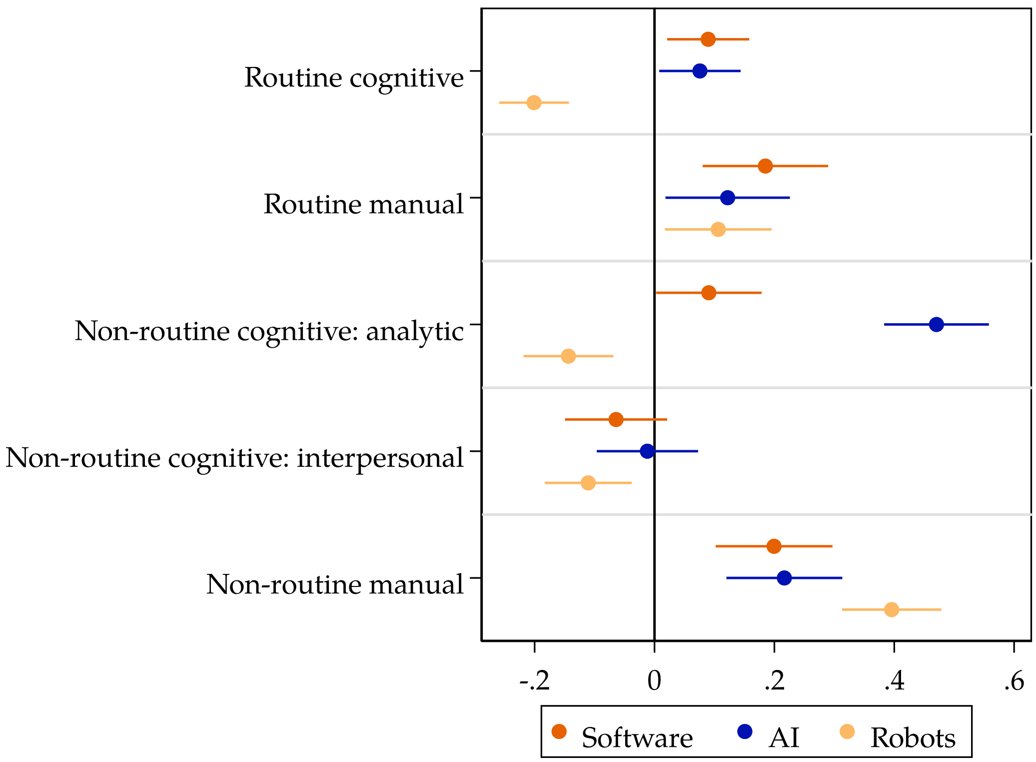

Figure A4: **Occupation-level regression results.**

Notes: Plot shows the coefficient estimates and 95% confidence intervals from each of three regressions, one per technology. The specification is $Exposure_{i,t} = RoutineCog_i + RoutineMan_i + NonRoutineCogA_i + NonRoutineCogI_i + NonRoutineMan_i + \epsilon_{i,t}$, where i indexes occupation, t indexes technology, and $Exposure_{i,t}$ measures the intensity of patenting in technology t directed towards the capabilities involved in occupation i. Exposure scores and routineness measures are each standardized to have a mean of zero and a cross-occupation standard deviation of one. For the standardizations and regressions, observations are weighted by employment reported in the May 2016 Occupational Employment Statistics. Each regression has $n = 961$ occupations, and the R^2 statistics are 14.1%, 14.7%, and 38.2% for software, AI, and robots respectively.

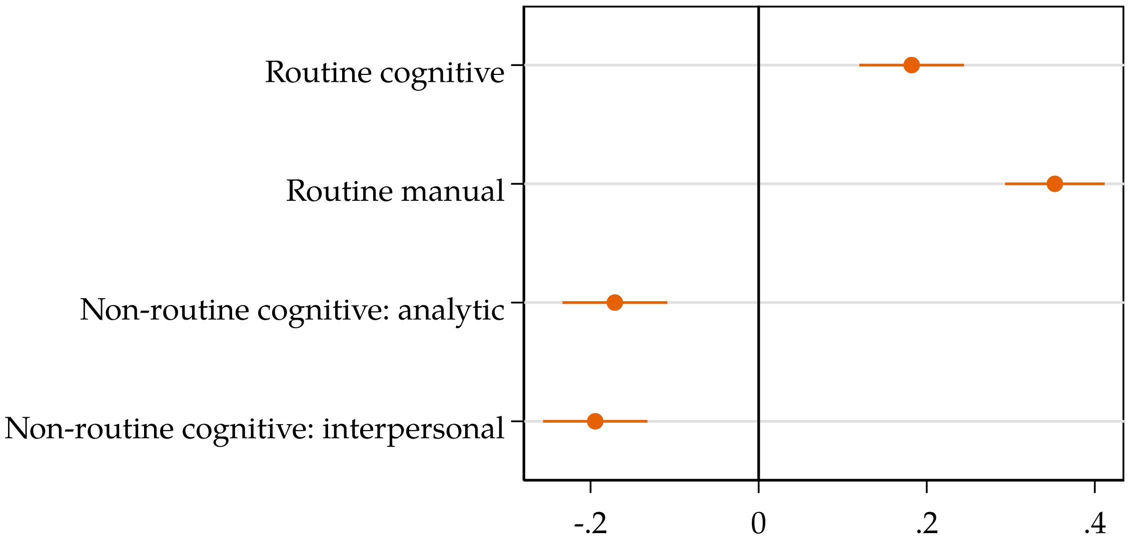

Figure A5: **Simple linear regression results for software.**

Notes: Plot shows the coefficient estimates and 95% confidence intervals from four simple linear regressions. Occupation-level routineness scores defined in Acemoglu and Autor (2011), which are updated versions of those in Autor, Levy, and Murnane (2003), are regressed on standardized occupation-level exposure scores calculated from software patent text and O*NET data. The routineness scores are functions of quantitative occupational characteristic scores provided in O*NET, as described in Section D.2. The specifications are $RoutineCognitive_i = Exposure_{i,Software} + \epsilon_i$, $RoutineManual_i = Exposure_{i,Software} + \epsilon_i$, and so on, where i indexes occupation. Observations are weighted by employment reported in the May 2016 Occupational Employment Statistics. Each regression has 961 observations, and the R^2 statistics are 3.3%, 12.4%, 2.9%, and 3.8% for the routine cognitive, routine manual, non-routine cognitive analytic, and non-routine cognitive interpersonal regressions respectively.

that I develop in this paper. In each case, observations are occupations, and the independent variable is my software exposure score for each occupation. I regress each of the four occupation-level routine/non-routine scores used in Autor, Levy, and Murnane (2003) separately on my software exposure score. I find that routine manual scores have the strongest positive association with the software exposure score, followed by routine cognitive scores, while the association between the non-routine cognitive scores and the software exposure score is negative. In other words, occupations with high routine manual and routine cognitive scores make intensive use of capabilities that feature in software patents, while occupations with high non-routine cognitive scores do not make intensive use of such capabilities. My measure thus independently recovers the key qualitative results of the Autor, Levy, and Murnane (2003) framework, i.e., the substitutability of software for routine cognitive and routine manual occupations, using only patent text and job descriptions as input.

D.2 Construction of routine/non-routine occupation measures

The creators of the O*NET database score each occupation along many characteristics, such as the extent to which it involves "being exact or accurate" or "coaching/developing others". These measures were hand-combined by Acemoglu and Autor (2011), updating Autor, Levy, and Murnane (2003), into composite "routine" (i.e., software-amenable) and "non-routine" scores for each occupation. We use these measures to characterize our exposure scores at various points in the text. The component O*NET scales used to produce each score are as follows:

Routine cognitive	4.C.3.b.7 Importance of repeating the same tasks
	4.C.3.b.4 Importance of being exact or accurate
	4.C.3.b.8 Structured v. Unstructured work (reverse)
Routine manual	4.C.3.d.3 Pace determined by speed of equipment
	4.A.3.a.3 Controlling machines and processes
	4.C.2.d.1.i Spend time making repetitive motions
Non-routine cognitive: analytic	4.A.2.a.4 Analyzing data/information
	4.A.2.b.2 Thinking creatively
	4.A.4.a.1 Interpreting information for others
Non-routine cognitive: interpersonal	4.A.4.a.4 Establishing and maintaining personal relationships
	4.A.4.b.4 Guiding, directing and motivating subordinates
	4.A.4.b.5 Coaching/developing others
Non-routine manual	4.A.3.a.4 Operating vehicles, mechanized devices, or equipment
	1.A.2.a.2 Manual dexterity
	1.A.1.f.1 Spatial orientation
	4.C.2.d.1.g Spend time using hands to handle, control or feel objects, tools or controls

I use the replication code provided for Acemoglu and Autor (2011) to generate these measures for O*NET v22.0.