The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization

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Abstract

Although artificial intelligence (AI) promises to spur economic growth, there is widespread concern that it may replace human labor. We investigate the link between AI and labor by creating a new measure that we call the AI Occupational Impact (AIOI). The AIOI measure links advances in specific applications of AI, such as image recognition, translation, or the ability to play strategic games, to workplace abilities and occupations. We use this measure to study the relationship between AI and wages, employment, and labor market polarization. We provide evidence that, on average, occupations impacted by AI experience a small but positive change in wages, but no change in employment. We also provide evidence that the positive correlation with wages is driven primarily by occupations with higher software skill requirements, and that higher-income occupations have a strong positive relationship between our measure of AI impact and both employment and wages. These findings suggest that access to complementary skills and technologies may play an important role in determining the impact of AI, and that AI has the potential to exacerbate labor market polarization.

Keywords: artificial intelligence, employment, job polarization, labor, wages

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1. Introduction

Recent advances in artificial intelligence (AI) have generated excitement about AI's potential to spur economic growth. This is welcome news given that 36 of 37 advanced economies had slower productivity growth from 2006 to 2016 than from 1996 to 2006 and the average growth rate in these countries fell from 2.7 percent to 1.0 percent over the same time period (Furman and Seamans 2019). The data-heavy, algorithmic approach of artificial intelligence has applications in multiple domains in the economy (Agarwal and Dhar 2014, Agrawal et al. 2019), and scholars believe that AI has the potential to be "the most important general-purpose technology of our era" (Brynjolfsson and McAfee 2017). However, there is concern that advances in AI will lead to mass automation and job losses.

The question of whether AI complements or substitutes for human labor is an important one with policy implications. For example, if AI substitutes for human labor, policymakers may want to consider reskilling or retraining programs for affected individuals or more radical policies such as universal basic income (Hoynes and Rothstein 2019). On the other hand, if AI complements human labor and spurs growth, policymakers may instead favor policies to encourage AI investment. There are a number of case studies appearing in the popular press, some describing AI as a substitute for labor, others describing AI as a complement (e.g., Agrawal et al. 2017, Levy 2018, Tangermann 2019). However, there is very little systematic evidence on the impact of AI on labor. Part of the reason for the lack of evidence is that the rapid advancement in AI is a nascent phenomenon, and accordingly, appropriate tools to measure its impact have yet to be developed (McElheran 2018, Raj and Seamans 2018).

In order to fill this gap, we develop a new measure of the impact of AI on occupations that we call the AI Occupational Impact (AIOI) and then apply this measure to study the impact of AI on various employment outcomes. The AIOI measure relies on a modified version of a method described by Felten, Raj, and Seamans (2018) that links specific applications of AI to different occupation-level abilities. Artificial intelligence is a construct with varying definitions and interpretations: "general" AI refers to computer software that can think and act on its own, which does not yet exist; "narrow" AI refers to computer software that relies on highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future (Raj and Seamans 2019). Because narrow AI algorithms "learn" from existing data to improve performance, these techniques are often referred to as "machine learning." These machine learning techniques can be applied in a number of different functions.

In this project, we consider different functions or applications of narrow AI and use data from the Electronic Frontier Foundation, an organization that tracks reported progress on metrics of AI performance across separate AI applications, to measure advancement across a variety of AI functions over time. The crux of our method is the assumption that occupations that rely on abilities that are linked to applications of AI that have progressed faster are the occupations which have been more impacted by AI. We provide several validations of this assumption, including case studies of occupations and an examination of the adoption of occupational skills related to AI technologies using Burning Glass Labor Insight data.

We then use the AIOI measure to study the links between AI, wages, and employment. We find evidence that, despite broad concerns about AI's potential to substitute for labor, exposure to AI is not significantly related to employment growth, but is positively correlated with wage growth, on average. Specifically, an increase of one standard deviation in the AIOI is associated with a 0.41 percentage point increase in wage growth. We find that the increase in wage growth in response to advances in AI is largely driven by occupations that require a high level of familiarity with software. Occupations that require a low or medium level of familiarity with software do not have a meaningful relationship between AIOI and wage growth; among high-software-prevalence occupations, however, a one standard deviation increase in AIOI is associated with a 0.61 percentage point increase in wage growth.

Firms can invest in and develop human capital through the education and training of their employees (Becker 1962, 1993), and task-specific human capital, defined as human capital accumulated through task-specific learning-by-doing, tends to be occupation-specific based on the abilities and work content of the job (Gibbons and Waldman 2004). We believe that our findings provide evidence that task-specific human capital, which we measure through exposure to and familiarity with software skills, may be instrumental in unlocking the complementarities of AI. These findings echo previous literature that suggests that software skills may be complementary to information technologies (Tambe 2014, Tambe and Hitt 2014), and suggests that the impact of AI may be similar to that of previous information technologies rather than being a tool for mass automation. In addition, these results are consistent with experimental evidence reported by Choudhury, Starr, and Agarwal (2019), which suggests that workers in occupations that feature a higher level of software usage may be more familiar with emerging AI technologies because the form and function of some AI technologies and software are also similar. Because of this familiarity, workers in those occupations are better able to take advantage of complementarities between AI and the tasks required by the occupation, leading to increased productivity and wage growth.

We also study the link between the AIOI and labor polarization. Although innovation has historically led to economic growth (Romer 1990, Solow 1957), it has at times substituted for human labor, and thus radical new technologies are often accompanied by anxiety about the fate of workers (Mokyr et al. 2015). Advances in computing and information technologies have sparked discussions around the welfare effects of skill-biased technical change, which favors high-skill labor while often disadvantaging middle- or low-skill labor (Berman et al. 1998, Card and DiNardo 2002). Autor, Levy, and Murnane (2003) suggest that high-skill occupations that use problem solving, intuition, and creativity, and low-skill jobs that require adaptability and face-to-face interaction are less easy to routinize and thus to automate. Autor and Dorn (2013) suggest that, because of this, middle-skill jobs are most vulnerable to displacement by robots and automation. This can lead to labor market polarization, where middle-skill, middle-income jobs are negatively affected by innovation, while low and high-skill occupations continue to grow.

Evidence regarding the emergence of labor market polarization is mixed. Goos, Manning, and Salomons (2009, 2014) find evidence of labor market polarization across European countries in the late 1990s through the early 2000s, while Autor (2015) and Mishel, Shierholz, and Schmitt (2013) suggest that labor market polarization rose in the 1980s and 1990s before declining in the 2000s. In addition, data from the 2000s suggest that higher-skilled occupations grew faster than lower- and middle-skill occupations (Council of Economic Advisers 2016). In particular, high-skill and widely traded occupations have experienced explosive wage growth from 1980 to 2015, increasing income inequality (Eckert et al. 2019). However, little research has established how recent advances in AI may affect labor market polarization. Big data and machine learning may facilitate automation of tasks that were previously difficult to automate (Frey and Osborne 2017), and there is some evidence that higher levels of robot density can lead to a decline in hours worked by low-skilled workers (Graetz and Michaels 2018). For high-income occupations, we find evidence that a one standard deviation increase in the AIOI measure is associated with a 3.94 percentage point increase in employment growth and a 1.40 percentage point increase in wage growth, but the AIOI has no meaningful relationship with employment or wage growth for low- or middle-income occupations. Our findings indicate that the benefits of AI technologies may be concentrated among high-income occupations and that AI could exacerbate income inequality or labor market polarization.

Our paper contributes to multiple literatures. It is most closely related to two recent papers that provide measures of the impact of new technologies on occupations (e.g., Brynjolfsson et al. 2018, Frey and Osborne 2017). Brynjolfsson, Mitchell, and Rock (2018) measure the extent to which machine learning can substitute for tasks required in an occupation. Frey and Osborne (2017) predict the percentage of tasks within an occupation that will be automated (by AI or other types of technologies) in the near future. We provide a more in-depth discussion of how our work complements these two earlier studies in the discussion section of the paper.

More broadly, our paper is related to recent empirical research on the impact of AI on labor, including that by Fossen and Sorgner (2019a), who use Current Population Survey data to study job stability and occupation switching; Choudhury et al. (2019), who use an experimental design to study how AI assists patent examiners in the US Patent and Trademark Office; and Cowgill (2019), who studies how machine learning can be used to improve hiring and recruitment routines. Our paper is also related to studies of the conditions under which new technologies complement labor (e.g., Aral et al. 2012, Avgar et al. 2018, Choudhury et al. 2019, Dranove et al. 2014). Further, our work contributes to a substantial literature on how automation affects workers (e.g., Acemoglu and Autor 2011, Autor 2015, Autor et al. 2003). For example, a recent paper in this area by Bessen et al. (2019) uses Dutch micro-data to study how the adoption of automating technologies affects a firm’s workers.

Our work is also related to the effects of robots on labor. While robots and AI differ in multiple ways, both have experienced rapid advancements in recent years, have seen commercial applications increase dramatically, and have the potential to seriously affect labor (Furman and Seamans 2019). Several recent papers studying the effects of robots on labor have found mixed results. For example, Graetz and Michaels (2018) find no significant relationship between robots and employment across 17 countries between 1993 and 2007; Acemoglu and Restrepo (2018) find a negative relationship between robots and employment in the United States between 1990 and 2007; and Dixon, Hong, and Wu (2019) find a positive relationship between robots and employment in Canadian manufacturing firms between 2001 and 2006.

The paper proceeds as follows. In the second section we describe the methodology that we use to construct the AI Occupational Impact (AIOI) measure. In the third section we describe the steps we take to validate our methodology and resulting AIOI measure. In the fourth section we use the AIOI to study how AI has impacted wages, employment, and labor market polarization. In the fifth section we conclude with a discussion about how our measure compares with other measures of AI and describe other potential applications of AIOI.

2. Construction of the AI Occupational Impact (AIOI) Measure

Our methodology isolates the impact of advances in specific functions of AI on occupational abilities and creates a measure of the aggregate impact of AI at the occupation level by looking at the abilities used within an occupation. Our analytical strategy borrows heavily from Felten et al.'s (2018) methodology, though we make changes to the method to account for the scope of abilities required in each occupation. We consider "labor" as the bundle of skills and abilities that are used within a specific occupation (Autor and Handel 2013), and this "micro" approach allows us to examine how AI may impact the abilities that each occupation requires.

We link advances in specific functions of AI to different types of abilities in the U.S. workforce using a crowd-sourced dataset; then, considering the work content of each occupation, we aggregate the ability-level impact of advances in AI subfunctions at the occupation level.

2.1. Data

For the construction of the AIOI, we rely on two independent databases: the Electronic Frontier Foundation (EFF) AI Progress Measurement dataset and the Occupational Information Network (O*NET) database developed by the United States Department of Labor. The EFF AI Progress Measurement project tracks reported progress on metrics of AI performance across separate artificial intelligence applications, such as image recognition, speech recognition, translation, or abstract strategy games. For each application, the EFF monitors progress in the field by drawing on data from multiple sources, including academic literature, review articles, blog posts, and websites focused on artificial intelligence, and the EFF only includes data from verified sources that document proof of their findings (AI Progress Measurement 2019). For the purposes of this study, we focus on the nine AI applications for which the EFF has sufficient data to measure progress in the technology from 2010 to 2015.

The O*NET database defines and describes professions in the modern-day American workplace (O*NET® Database Releases Archive at O*NET Resource Center 2019). For each occupation, classified at the eight-digit Standard Occupational Classification (SOC) level, O*NET provides information regarding work characteristics, experience requirements, job responsibilities, and the state of the labor market. O*NET data is frequently used to measure occupational work or task content in academic research (e.g., Autor and Handel 2013, Brynjolfsson et al. 2018, Goos et al. 2009). The O*NET dataset is hosted and organized by the Department of Labor and is updated continuously as occupations change over time based on information that the Department of Labor collects from job incumbents, occupational experts, analysts, professional organizations, and job postings.

For the purposes of our analysis, we focus on the 52 distinct abilities O*NET uses to describe the workplace activities of each occupation within the O*NET database. O*NET notes both the importance and the level or prevalence of each ability within an occupation (using a 1–5 and 1–7 scale respectively). For each occupation, O*NET also provides a list of skills and work activities. However, we focus primarily on abilities because O*NET defines these as "enduring attributes of the individual that influence performance." Skills and work activities, on the other hand, are respectively defined as "developed capacities that facilitate learning or the more rapid acquisition of knowledge" and "general types of job behaviors occurring on multiple jobs" (O*NET Online 2019).[1] Thus, abilities are designed to capture something more fundamental about what an individual brings to a given occupation.

2.2 Methodology

We construct the AIOI using data from the nine EFF AI applications that contain enough information available at the time of writing to measure clear progress in the metric from 2010 onward: abstract strategy games, real-time video games, image recognition, visual question answering, image generation, reading comprehension, language modeling, translation, and speech recognition. The EFF often tracks several metrics within an application. To calculate the rate of progress within each application, we first scale each metric to account for the exponential rate of progress in the technology seen in the data. For example, if a metric measures the error rate on a task, we take the negative logarithm of the metric to arrive at a scaled figure that will grow linearly as the error rate decreases exponentially. Within each application, we then

[1] For example "deductive reasoning" is an ability, while "management of personnel resources" is a skill and "selling or influencing others" is a work activity.

calculate the average rate of progress by fitting a linear model across the scaled metrics. We focus on progress made from 2010 to 2015 and calculate the rate of progress within each application based on metrics within that time range. Table 1 presents the calculated rate of progress for each AI application along with the definition used by the EFF.

TABLE 1 HERE

We next link the rate of progress across the nine EFF AI applications with the set of 52 abilities in the O*NET database using approximately 1,800 survey responses from "gig workers" from Amazon's Mechanical Turk (mTurk) web service. mTurk functions as a crowdsourced internet marketplace allowing payment for the completion of tasks by workers. Crowdsourcing platforms such as mTurk have increasingly been used to construct datasets for academic research in the field of information systems and management science (e.g., Brynjolfsson et al. 2018, Kim and Luca 2019). Although the use of these tools may raise concerns about external validity, prior work suggests that surveys and experiments executed through online labor market platforms, such as mTurk, are largely generalizable to in-person or laboratory settings (Horton et al. 2011). We rely on these mTurk survey responses to construct a matrix connecting the EFF AI Progress Measurement data to the O*NET occupation-level ability data.

To link the EFF AI applications to workplace abilities, for each of the nine EFF AI applications considered in our analysis (abstract strategy games, real-time video games, image recognition, visual question answering, image generation, reading comprehension, language modeling, translation, and speech recognition) we survey a sample of 200 mTurkers residing in the United States. Each respondent is asked to consider how the AI application is related to each of the 52 abilities considered by O*NET in its occupational definitions. The survey provides descriptions of the AI application from EFF as well as definitions of the O*NET abilities; for each ability we ask respondents to answer Yes or No based on whether they believe that the application is related to or could be used for each ability. We opt for a simple Yes or No question for simplicity and to limit the extent to which participants can express their own biases regarding what form AI impact may have, as our measure is designed to be agnostic to whether AI is a complement to or substitute for labor. An example of a question used for “image recognition” is presented in *Appendix Figure A1*.

Respondents are paid $1 upon completion of the survey, which is designed to take five to ten minutes to complete. The questions are identical for each application-ability combination except for the definitions presented. The order of the abilities presented to the respondent is randomized, and an attention check question is included in the middle portion of the survey. Respondents that fail the attention check or do not complete the survey entirely are removed from the sample. In addition, using the mTurk platform, we collect background information on respondents regarding the highest level of education achieved and the specific academic field in which they obtained their highest degree.

We operationalize the survey data by coding Yes or No responses as a binary variable. Across each application-ability combination, we average the binary measure to construct a measure of how related the AI applications are to the ability. We organize this measure of application-ability relatedness into a matrix that connects the nine separate EFF AI metrics to the 52 O*NET occupational abilities. Through this matrix, we translate progress as measured by the EFF within each AI application to O*NET abilities by multiplying the calculated rate of progress for the application by the measure of application-ability relatedness for each of the 52 abilities. We then calculate an ability-level AI impact by summing this product across the nine AI applications for each ability. By calculating the ability-level AI impact with a sum across the AI applications, we are assuming that each application has an independent effect on an ability and do not consider interactions across applications. Although this may be a limitation, considering the myriad of ways in which the applications could interact would be infeasible.

We next use the O*NET occupational definitions to evaluate the impact of the AI technology on each occupation. We rely on the O*NET 14.0 database released in June 2009, as it is the last update to the O*NET data prior to 2010 when we begin to measure progress in the AI applications. We weight the ability-level AI impact by the ability's prevalence and importance within each occupation as measured by O*NET by multiplying the ability-level AI impact by the scaled prevalence and importance scores for that ability within each occupation; we measure the aggregate impact of AI on an occupation by summing this weighted ability-level AI impact across all abilities in an occupation.[2]

In an adjustment to Felten et al.'s (2018) methodology, we scale the aggregated impact of AI across all abilities by the weighted sum of the prevalence and importance of all abilities used in the occupation to account for the total required ability set within an occupation. We believe this adjustment is important due to the nature of the O*NET definitions. Some occupations as defined by O*NET have many abilities that are considered important and prevalent, while others contain a smaller number. Hence, without the adjustment based on the weighted sum of all abilities, our methodology would overweight the impact of AI on broader occupations that require more abilities. The adjustment, therefore, accounts for the different scope of occupations and more accurately measures the relative impact that AI may have on an occupation.

[2] There is a high correlation between an occupation's prevalence and importance scores. The AIOI scores obtained at the occupation level are robust to using either prevalence or importance alone to weight the ability-level AI impact.

Finally, we collapse the AIOI to occupations at the six-digit SOC level to align with the other major data sources we use in additional analyses. The O*NET data are organized at the eight-digit SOC level; however, because the vast majority of eight-digit SOC classifications contain only one six-digit SOC classification, this change does not alter our sample size greatly. We collapse the 832 occupations at the eight-digit SOC level to 742 occupations at the six-digit SOC level by calculating the mean AIOI across all occupations defined by O*NET within the six-digit SOC level. Although we lose granularity with some occupations through this transformation, it more easily allows us to use the AIOI in additional analyses. Ultimately, our methodology produces a score that measures how advances in AI from 2010 to 2015 are related to occupations at the six-digit SOC level based on their ability composition as defined by O*NET.

We note that the methodology is flexible. The AIOI can be updated based on the changing occupational descriptions and definitions provided by the O*NET database, as well as continued progress in the AI applications as measured by the EFF. A complete list of occupations and the associated AIOI scores based on measured progress in AI applications by the EFF from 2010 to 2015 is in *Appendix B.* In the following section, we qualitatively and quantitatively analyze and validate the AIOI scores.

3. Validation of the Artificial Intelligence Occupation Impact Scores

Owing to the novel nature of our methodology and the limited research in this area, validation of the metric presents challenges since there are no clear benchmarks to test the AIOI scores against. It is unclear how one might expect the impact of AI to manifest itself in occupations while remaining agnostic about its effect on occupations and patterns of adoption, and most existing metrics to measure occupation-level impact of AI seek to determine the likelihood of substitution (Brynjolfsson et al. 2018, Frey and Osborne 2017). Given these challenges, we validate the AIOI scores in several ways. First, as an initial "gut check," we qualitatively discuss the differences across occupations that receive the highest and lowest scores in our sample. Second, we provide a deeper discussion for several occupations, including some that are often associated with advances in AI such as taxi drivers and long-haul truck drivers, to provide a sense of how advances in AI are affecting occupational abilities. Third, we present robustness checks for the construction of our matrix that connects AI applications to abilities. Fourth, we present evidence that the AIOI is positively associated with an increase in the use of AI skills within an occupation.

3.1 Most- and Least-Affected Occupations

To begin to understand the nature of the AIOI scores, we first compare the highest-scoring occupations with the lowest-scoring occupations. Table 2 presents the twenty occupations with the highest and lowest AIOI scores in our sample.

TABLE 2 HERE

The highest-scoring occupations (i.e., the ones that the AIOI predicts are most affected by AI based on technological progress from 2010 to 2015) consist almost entirely of white-collar occupations that require advanced degrees, such as civil engineers, actuaries, and epidemiologists. On the other hand, the lowest-scoring occupations largely are non-office jobs that require a high degree of physical effort and exertion, such as dancers, fitness trainers and aerobics instructors, and brickmasons and blockmasons. Intuitively, these rankings reflect our aim to isolate the impact of advances in AI. Whereas robotic technologies often involve physical manipulation and are capable of carrying out complex manual tasks, AI technologies are largely software-based and rely on iterative learning and perception (Raj and Seamans 2019).

Accordingly, we would expect AI to have a limited influence on the role of physical abilities in occupations.

The ability-level AI impact we calculate using our methodology reflects our aim to isolate the impact of advances in AI as well. The five least-affected abilities as calculated through our metric are stamina, explosive strength, static strength, dynamic strength, and trunk strength. These abilities are all classified by O*NET as physical abilities, defined as abilities that "influence strength, endurance, flexibility, balance, and coordination" (O*NET Online 2019). In fact, the nine physical abilities as classified by O*NET are the nine least-affected abilities as measured using our methodology. On the other hand, the most-affected abilities tend to be classified as cognitive abilities, defined as abilities that "influence the acquisition and application of knowledge in problem solving" (O*NET Online 2019). The five most-affected abilities are information ordering, memorization, perceptual speed, speed of closure (referring to the speed in pattern detection), and flexibility of closure (referring to the acuity in pattern detection), and are all classified by O*NET as cognitive abilities.

The AIOI scores reflect that AI will have a larger impact on cognitive abilities and tasks that involve problem solving and perception and a smaller influence on physical tasks and abilities. We believe that this relationship is in line with current scientific perceptions of AI technologies (e.g., Brynjolfsson and McAfee 2014, Brynjolfsson and Mitchell 2017) and accordingly provides a measure of support for our methodology.

3.2 Discussion of Selected Occupations

We next turn to a discussion of selected occupations. We start by comparing and contrasting the scores of two occupations that require similar abilities but have disparate AI impact scores — surgeons and meat slaughterers — before discussing two occupations that are frequently discussed in the context of AI — truck drivers and taxi drivers.

3.2.1 Surgeons and Slaughterers

We attempt to provide more context for the AIOI scores by comparing two professions that share some similarities in terms of the ability set required yet have highly disparate AIOI scores — surgeons and meat slaughterers. Superficially, we might expect these occupations to have similar AIOI scores, as both require deft physical manipulation of human or animal tissue. While the two occupations require similar physical abilities, such as manual dexterity, finger dexterity, and arm-hand steadiness, the occupations' AIOI scores suggest that surgeons are far more affected by AI than meat slaughterers. The AIOI score for surgeons is at the 52nd percentile in relation to other occupations in our sample, while the AIOI score for slaughterers and meat packers is the 11th least-affected occupation and is at the 2nd percentile in our sample.

The difference between the AIOI scores in these two occupations seems to arise from the cognitive abilities required by each occupation. Although the two occupations require similar physical abilities, a number of cognitive abilities related to problem solving, such as problem sensitivity, deductive and inductive reasoning, flexibility of closure, and information ordering, are highly important for surgeons and are not imperative for meat slaughterers. Our methodology suggests that the impact of AI on occupations largely stems from these cognitive abilities; accordingly, surgeons have a much higher AIOI score than meat slaughterers despite utilizing a similar suite of physical abilities.

This comparison emphasizes that the AIOI suggests that AI will have a far larger impact on professions that rely primarily on cognitive abilities than on those that rely on physical abilities. We can expect that occupations that require a greater amount of problem solving, logical reasoning, and perception are more likely to be affected by AI than occupations that are largely rooted in physical abilities. Given the limited impact of AI on physical abilities, therefore, occupations with similar sets of physical abilities need not be impacted similarly by AI. Rather, occupations that require a similar set of cognitive or psychomotor abilities are more likely to have similar AIOI scores.

3.2.2 Truck Drivers and Taxi Drivers

Certain occupations are often considered to be particularly susceptible to advances in AI by the media and scholars. For example, AI technologies have shown the potential to outperform radiologists in detecting some abnormalities in x-rays, which has led to much debate regarding how AI may impact radiology as an occupation in the future (e.g., Agrawal et al. 2019, Hosny et al. 2018, Jha and Topol 2016, Pakdemirli 2019). The O*NET 14.0 database used in the construction of the AIOI scores does not contain data on workplace abilities required by radiologists specifically;[3] however, we instead focus on two other occupations that have also been discussed frequently in the context of AI — truck drivers and taxi drivers (e.g., Brynjolfsson et al. 2017, Mochizuki 2019, O’Brien 2019, Vanian 2017). AI technologies in the trucking and taxi industries offer large potential benefits in terms of risk and cost reduction (Brynjolfsson et al. 2017), and advances in AI-based autonomous vehicle technology have led some to believe that these occupations are likely to be disrupted as advances in AI continue to be made (Murphy 2017, Rea et al. 2017).

Despite these concerns, long-haul truck drivers and taxi drivers do not receive particularly high AIOI scores. Long-haul truck drivers have an AIOI score at the 16th percentile in relation to all other occupations in our sample, while taxi drivers and chauffeurs are at the 48th

[3] Radiation Therapists and Radiation Technologists are related occupations but are ultimately quite different in terms of the abilities required and their task composition.

percentile. In some respects, this may seem surprising. Both occupations require some abilities that are highly affected by AI according to our methodology, such as problem sensitivity and control precision, and advances in self-driving car technologies may lead some to believe that these occupations are particularly susceptible to disruption. The relatively low AIOI scores for the occupations may be driven in part by our decision to focus on the impact of just AI technologies instead of both AI and robotics technologies.

While the AIOI captures the impact of purely AI technologies on occupational abilities and tasks, it does not capture advances in robotics technologies. While autonomous vehicles integrate AI technologies, the driving component itself relies on robotics. Thus, while the AIOI can capture how certain abilities used by truck and taxi drivers may be affected by advances in AI (for example, the cognitive abilities required in constructing a route, psychomotor abilities involved in precision steering, or the sensory abilities required in depth perception), it does not capture how the interaction between advanced AI and robotics technologies affects abilities or occupations. Given the large role that physical manipulation and robotics technologies currently have in these occupations, the AIOI suggests that AI itself is unlikely to have an outsized impact on these occupations. While our sole focus on AI technologies is a limitation to our analysis in some cases, we believe that it is important to be able to isolate the impact of AI technologies and robotics technologies on the labor market and occupation rather than speaking of the two different technologies interchangeably. Further, our focus on separate applications of AI allows for a more targeted approach that is able to disentangle which applications are particularly likely to affect occupations.

3.3 Quantitative Robustness and Validation of the AI Impact Scores

In addition to our qualitative review of occupations and their AIOI scores, we test for the robustness of our AIOI scores and seek to validate the measure quantitatively. One key component of our methodology is the matrix constructed using mTurk survey data to connect progress in the tracked EFF AI applications with the 52 O*NET abilities. As a robustness check for this matrix, we rely on Amazon-provided data on the educational backgrounds of survey respondents. We compare the matrix used in our analysis to matrices constructed using samples of only those who completed a graduate degree program and only those who received their highest degree in computer science or engineering. The correlations across the different samples are broken down by EFF AI application in Table 3 and by O*NET ability in Table 4.

TABLES 3 AND 4 HERE

We find a high degree of correspondence across the matrices, as shown by the correlations between the scores of the survey responses for each EFF AI application and O*NET ability for the different subsamples. These findings suggest that the AIOI scores are unlikely to be sensitive to using subsamples of highly educated individuals or individuals with a background in computer science or engineering who are likely to have greater knowledge regarding AI.

As an additional validation exercise, we evaluate the relationship between the AIOI measure and changes in job descriptions and skills from 2010 to 2016 using Labor Insight data from Burning Glass Technologies. The proprietary Labor Insight data from Burning Glass provide labor market information by compiling internet job postings from more than 40,000 publicly available sources, such as internet job boards and corporate websites. Burning Glass uses AI technology to analyze the job postings and provide insight into labor market patterns. The data classify each job posting using the O*NET occupational classifications and provide a list and taxonomy of requirements for each job posting. The Burning Glass data allow us to track how job descriptions and skills change across occupations over time.

We use the Burning Glass data to measure how the demand for AI skills — which we define as skills within the Burning Glass skill clusters of Artificial Intelligence, Machine Learning, and Natural Language Processing — in an occupation changes over time. We calculate the change in the average count of these skills required in job postings for each occupation from 2010 to 2016. Presumably, occupations for which AI skills increase are quicker to adopt AI technologies and are more likely to be affected by AI. Figure 1 presents a scatter plot showing the relationship between the change in AI skills from 2010 to 2016 winsorized at the 1 percent and 99 percent level and the constructed AIOI scores.

FIGURE 1 HERE

Although the relationship is noisy, there is a clear positive relationship between the AIOI and the change in AI skills from 2010 to 2016, with a correlation coefficient of 0.228 *(p=0.000)*. In order to more systematically evaluate the relationship between the AIOI and the change in AI skills, we run a linear regression at the occupation level to measure the relationship between the AI impact score and the average change in AI skills from 2010 to 2016. Our model takes the following form:

$$Y_{\mathrm{i}} = \beta_0 + \beta_1 \, AIOI\ Score_i + \beta_2 X_i + \varepsilon_i,$$

where Y is the average change in AI skills from 2010 to 2016 for an occupation, X is a matrix of occupation-level control variables, and i indexes the occupation. Using the O*NET data, we construct two measures that we use in our matrix of control variables, X. For our control variables, we use O*NET-provided information about the *Degree of Automation* and the *Importance of Programming* at the occupation level. The *Degree of Automation* variable measures to what extent the job is automated, and the *Importance of Programming* variable measures the importance of writing computer programs for the occupation. For each of these skills and characteristics, O*NET assigns a value from 1 to 5 for each occupation, constructed using a weighted average of survey responses from occupational experts and incumbent employees, which we scale from 20 to 100. We use these variables as controls in our analysis to account for the level of exposure to and use of computer-based technologies.[4] We use Huber-White robust standard errors to account for heteroskedasticity in the error term. The coefficient of interest, β_1, captures the relationship between the AIOI score and the outcome of interest, the change in AI skill within an occupation from 2010 to 2016. Table 5 presents the results of this analysis.

TABLE 5 HERE

Even controlling for a number of occupation-level characteristics, such as the O*NET-provided degree-of-automation or importance-of-programming scores, the relationship between the AIOI and the change in AI skills remains large and statistically significant ($p<0.001$). We believe the statistical relationship between our AI impact score and the change in AI skills between 2010 and 2016 provides suggestive evidence that the AIOI is able to capture the influence of AI on an occupation. Importantly, this analysis also suggests that the AIOI is related to AI technology adoption, a vital consideration as we begin to consider the relationship between the AIOI and employment and wages. We next turn to our empirical strategy for investigating the relationship between AI impact and wages and labor.

[4] Using the O*NET data, we have constructed a number of other controls that similarly measure degree of technology exposure and use, including *Importance of Working with Computers* and *Importance of Controlling Machines.* Because there is a high degree of correlation between control measures, we include only *Degree of Automation* and *Importance of Programming* in the analysis. Results are robust to substituting these alternative control measures.

4. Artificial Intelligence and Employment and Wage Growth

4.1 Empirical Model

Although our occupation-level score measures the impact of AI on an occupation, it does not suggest what form that impact takes or the extent to which AI is complementary to or a substitute for labor. To shed light on these issues, we adopt a more granular approach that uses employment and wage data from the Bureau of Labor Statistics (BLS) for each occupation, at the state level, from 2010 to 2016. We then conduct regression analyses to identify how changes in wages and employment at the occupation-state level relate to the AIOI.

We conduct our analysis at the state level as it allows us to control for heterogeneity in occupations across states, particularly those arising from differences in occupational licensing laws across states. Kleiner and Krueger (2010) report that occupational licensing laws affect nearly 30 percent of the US labor force, and that over 1,100 occupations are licensed in at least one state. A variety of research finds that these laws affect wages and employment (see, e.g., Farronata et al. 2019). We therefore control for state-level variation in laws and regulations with a state-level fixed effect. We also control for occupational characteristics using the O*NET and Burning Glass data that we believe may be related both to the adoption and use of AI and to growth in employment and wages within an occupation.

The regression models that we use take the following form:

$$Y_{\text{is}} = \beta_0 + \beta_1 \, AIOI\ Score_i + \beta_2 X_i + \gamma_s + \varepsilon_{is}$$

where *Y* is Employment Growth or Wage Growth from 2010 to 2016, *X* is a vector of occupation-level control variables, γ is a fixed effect for the state, *i* indexes the occupation, and *s* indexes the state. Errors are clustered at the state level. The coefficient of interest, β_1, captures the relationship between AIOI and the outcomes of interest, employment or wage growth. For some sets of results, we run separate sets of regressions for terciles of software use and median income, as described below.

4.2 Data and variables

Dependent variables. We use data from the BLS's Occupational Employment Statistics database to construct two dependent variables. $Employment\ Growth_{is}$ is the percentage change in employment from 2010 to 2016 for each occupation in each state. $Wage\ Growth_{is}$ is the percentage change in median wages from 2010 to 2016 for each occupation in each state. We note that these dependent variables do not allow us to see the emergence of new occupations or the complete removal of others within a state. For example, completely new occupations that are created owing to innovation or technological change will not be captured, since the SOC codes used to organize occupations in the dependent variable and in our AIOI are not updated from 2010 to 2016. In addition, if a small or highly specialized occupation has employment within a state in 2010 but not in 2016 (or vice versa), it will not be in our data. Despite these limitations, these dependent measures allow us to examine within-occupation changes in employment and wages at the state level over time. We assume that a positive correlation between the dependent measures and AIOI suggests that AI may be associated with an increase in labor productivity, leading to growth in wages and employment, and is complementary to labor. On the other hand, we assume that a negative correlation between the dependent measures and the AIOI suggests that AI may substitute for labor and reduce employment and wage growth.

Independent variables. Our main independent variable is the $AIOI\ Score_i$ described above. We use BLS, O*NET, and Burning Glass data to construct several additional variables.

First, using data from the BLS's Occupational Employment Statistics database, we construct a measure of employment and wage growth from 2005 to 2010 for each occupation at the state level. For each regression, we control for employment or wage growth from 2005 to 2010, depending on the dependent variable to account for pre-existing trends.

Second, we construct a variable using the Burning Glass data, which allow us to measure the prevalence of software skills required in occupations at the beginning of the time period. The Burning Glass data classify whether each skill involves the use of software. For each occupation, we construct the variable *Proportion of Software Skills*, which is the average proportion of software skills specified in 2010 job postings. We assume that occupations with a higher proportion of software skills will feature a higher use of technologies that are related and relevant to artificial intelligence technologies. We believe this is reasonable given the role of software in intelligent computing and that many emerging forms of artificial intelligence technologies take the form of software (e.g., Buchanan 2005, Menzies 2003, Norvig and Russell 1994), and literature suggests that software skills can be complementary to information technologies (Tambe 2014, Tambe and Hitt 2014).

Finally, as described above, we construct two additional occupational characteristic variables using O*NET data — *Degree of Automation* and *Importance of Programming*. In some of our regressions, we include the variable *State Population Change*, which we obtain from the publicly available Federal Reserve Economic Data (FRED) database (we do not include this variable in regressions that use state fixed effects). We present the summary statistics of all variables in Table 6.

TABLE 6 HERE

4.3 Results

4.3.1 Main Results

We first present our main analysis considering the relationship between AIOI and employment and wage growth. Table 7 shows the OLS estimates of the relationship between AI as measured by the AIOI score and employment growth (Columns 1–4) or wage growth (Columns 5–8) between 2010 and 2016. For each dependent variable, we first run a simple regression including the AIOI score and the measure of employment or wage growth from 2005 to 2010, then expand on the model by (1) adding a control for the change in a state's population between 2010 and 2016, (2) adding in state fixed effects, and finally (3) estimating a model containing the full set of controls outlined above, as well as state fixed effects.

TABLE 7 HERE

Consistent across all models, the lagged employment or wage growth is highly correlated with current employment or wage growth. This is not a surprise and helps account for many of the state-occupation-specific trends that may be influencing changes in the dependent variable of interest.

The regression estimates in Columns 1–4 indicate that AIOI does not have a meaningful relationship with employment growth. Using the results from Column 4, we find that the AIOI has a positive but statistically insignificant relationship with employment growth. On the other hand, the regression estimates in Columns 5–8 indicate that AIOI has a positive and statistically significant relationship with wage growth. Because the AIOI measure is arbitrary, we consider how a change in one standard deviation in the AIOI score is associated with wage growth to understand the magnitude of the result — this is approximately the difference between the highest-scoring occupation in our sample (civil engineers) and the 246th ranked occupation by AIOI score (electrical and electronic engineering technicians). The results in Column 8 indicate that an increase of one standard deviation in the AIOI score is associated with an increase in wage growth of 0.41 percentage points (p<0.001). Scaling this estimate by the sample mean of median wage growth from 2010 to 2016, we find that a one standard deviation increase in the AIOI score is associated with a 3.5 percent increase in wage growth. To put this in context, Card (1999) reports that an additional year of education increases earnings by about 10 percent.

4.3.1 Heterogeneous Impact of AI

We next attempt to parse how the relationship between AI and employment and wage growth may differ depending on occupation-specific characteristics. We first consider how the presence of complementary skills and capabilities within an occupation alters the impact of AI and then examine how the relationship between AI and employment and wage growth differs across low-, middle-, and high-income occupations to identify how advances in AI may affect labor market polarization.

4.3.1.1 Complementary Skills and Capabilities

To identify the presence of complementary skills, techniques, and capabilities within an occupation, we use the Burning Glass data to measure the prevalence of software skills required within an occupation in 2010. Using Burning Glass data, we classify occupations into terciles by the proportion of software skills required; we classify occupations in the top tercile as having high software prevalence, occupations in the middle tercile as having medium software prevalence, and occupations in the bottom quartile as having low software prevalence. As discussed above, we believe that exposure to software skills is especially relevant in this context given the relationship between AI and software, and the manifestation of many emerging AI tools as software (e.g., Buchanan 2005, Menzies 2003, Norvig and Russell 1994). We then run our preferred regression specification, with state fixed effects and the full set of controls, using employment and wage changes from 2010 to 2016 as our dependent variables, separately for occupations in each tercile.

TABLE 8 HERE

These results, presented in Table 8, suggest that the positive relationship between AI and wage growth is largely driven by occupations involving a high level of software skills. Although there is no statistically significant relationship between the AIOI and wage growth for low- or medium-software-prevalence occupations (Columns 4 and 5), there is a positive and significant relationship for high-software-prevalence occupations ($p<0.001$) (Column 6). An increase of one standard deviation in the AIOI score is associated with an increase in wage growth of 0.61 percentage points for high-software-prevalence occupations (in comparison with 0.41 percentage points for all occupations). Scaling by the sample mean for median wage growth for high-software-prevalence occupations from 2010 to 2016, we find that a one standard deviation increase in the AIOI score is associated with a 4.9 percent increase in median wage growth. There is no statistically significant relationship between the AIOI and employment growth for low-, medium-, or high-software-prevalence occupations (Columns 1, 2, and 3).

4.3.1.2 Labor Market Polarization

We next turn how AI may affect labor market polarization by considering how the relationship between employment and wage growth differs based on income. Based on the median annual income for an occupation in 2010, we split our sample of occupations into terciles. We classify occupations in the top tercile as high-income occupations, occupations in the middle tercile as middle-income occupations, and occupations in the bottom tercile as low-income occupations. Existing literature suggests that wages can be considered a proxy for skill in an occupation (Autor and Dorn 2013); thus, by categorizing occupations by wage, we can evaluate how AI may affect low-, medium-, and high-skill occupations and, accordingly, labor market polarization. We run our preferred regression specification, with state fixed effects and the full set of controls, using employment and wage changes for the period 2010–2016 as our dependent variables, separately for occupations in each tercile.

TABLE 9 HERE

The results, presented in Table 9, suggest that AI may have a particularly positive impact on high-income occupations. There is no significant relationship between the AIOI and employment and wage growth for low- and middle-income occupations (Columns 1, 2, 4, and 5); however, within the sample of high-income occupations, there is a strong and positive relationship between the AIOI and employment and wage growth (Columns 3 and 6). For high-income occupations, an increase of one standard deviation in the AIOI score is associated with an increase in employment growth of 3.94 percentage points (in comparison with the insignificant relationship between employment growth and AIOI in the sample of all occupations) and wage growth of 1.40 percentage points (in comparison with 0.41 percentage points in the sample of all occupations). Scaling by the sample mean for high-income occupations, this corresponds to a 22.6 percent increase in employment growth and a 12.0 percent increase in wage growth. These results are striking: although our analysis does not allow us to cleanly identify a causal effect, our measure of AI impact has a strong and positive correlation with employment and wage growth for high-income occupations but has no meaningful impact on low- or middle-income occupations. It is possible, therefore, that advances in AI may lead to greater growth in employment and wages for high-income occupations than for low- and middle-income occupations and could have troubling implications for income inequality.

5. Discussion

Despite excitement about AI's impact on the economy and concern about its effect on labor, there is little systematic evidence of either. Our study makes several contributions toward understanding these effects. First, we describe and validate a new methodology for linking advances in AI to human abilities. Second, using this methodology, we develop a measure of the impact of AI on an occupation, which we call the AI Occupational Impact (AIOI). We expect the new AIOI measure will be useful to other researchers interested in the link between AI and other labor-oriented outcomes, including employment and wages, regional-level outcomes such as inequality and unemployment, and potentially firm-level outcomes. Third, using the AIOI measure, we provide suggestive evidence that AI and human labor are complementary in many cases and that AI has a more positive impact on high-income occupations than on low- and middle-income occupations and, thus, may exacerbate income inequality. Much of the popular narrative around AI is that it will substitute for human labor, and thus we believe that our findings will be of particular interest not only to other researchers but also to policymakers and the broader public.

Our paper is closely related to two others that provide their own measures of the impact of new technology on occupations. Frey and Osborne (2017) provide a forward-looking prediction of which occupations will be fully or partly automated. Their approach differs from ours in three main ways. First, Frey and Osborne consider "automation" without specifying whether the automation occurs via AI, robots, sensors, or other type of technology, whereas our focus is only on AI. Second, Frey and Osborne's measure is forward-looking — it is the result of a Delphi-method process involving experts in automation — whereas our approach is backward-looking and considers advances in AI between 2010 and 2015. Third, Frey and Osborne specifically focus on the potential for new technologies to substitute for occupations, while the AIOI seeks to measure the aggregate impact of AI and is agnostic as to whether AI is a complement to or a substitute for labor.

Our work is also closely related to work by Brynjolfsson, Mitchell, and Rock (2018). Brynjolfsson et al. (2018) provide a measure of the extent to which machine learning can substitute for tasks in an occupation. However, their approach differs from ours in a number of ways. First, Brynjolfsson and co-authors focus broadly on machine learning, while we focus more specifically on different applications of AI, allowing us to isolate how advances in specific functions of the technology may impact abilities and occupations. Second, like Frey and Osborne (2017), Brynjolfsson et al. have a forward-looking approach that seeks to predict how machine learning will affect occupations, while our approach is backward-looking based on progress in AI applications from 2010 to 2015. Third, again, much like Frey and Osborne (2017), Brynjolfsson et al. are primarily focused on the extent to which machine learning can substitute for labor, whereas our approach allows us to be agnostic as to conditions under which AI is a substitute for or a complement to human labor.

These three approaches are complementary and can be useful to different researchers depending on the specific questions being asked. We believe our measure is probably best suited for studies that focus on the recent past (i.e., since 2010) and immediate future. The studies that we provide in this paper of AI's impact on wages, employment, and job polarization since 2010 are one example of the type of research that our measure can be used for. Other researchers have used different applications of the AIOI, including Fossen and Sorgner (2019b), who study how advances in AI create opportunities for growth-oriented entrepreneurship, and Goldfarb, Taska, and Teodoridis (2019), who use the AIOI to examine whether AI has the characteristics of a general-purpose technology within the healthcare industry.

Separately, the methodology we use to develop our AIOI measure can be applied in related work. Our methodology is dynamic, and the AIOI can be updated as the EFF continues to collect data on the progress of various AI applications and as O*NET updates occupational definitions. We believe that our approach also could be used as a forward-looking tool to predict how future advances in different applications of AI might affect different occupations or geographies. For example, we could simulate an arbitrary increase in any of the applications in AI (e.g., a 10 percent increase in speech recognition) and construct hypothetical AIOI scores based on the simulated increase. Using these hypothetical scores, we could identify the occupations that may be most affected and can use data from the Bureau of Labor Statistics to identify geographic areas that are most likely to be impacted by future advances. We believe this could be a tool for policymakers to identify the potentially most vulnerable occupations and geographies.

It is important to point out that the analyses we present using AIOI to study the link between AI and employment, wages, and job polarization have limitations. In particular, empirical identification is a major challenge. We measure the impact of AI in the same period that we collect data regarding AI progress. We believe this is appropriate, given our interest in capturing the effect of the advances in technology as they happen. Nonetheless, this makes it difficult to establish causality. In addition, advances in AI are not exogenous, and the AIOI may be linked to occupational characteristics that are also related to wage and employment growth during the relevant time period, also limiting our ability to identify a causal effect. Further, although we find that the AIOI has a strong and positive association with AI skills as measured by Burning Glass, there may be a lag between the advances in the technology and its adoption and effect in the labor market. We do not examine this; however, future research could seek to identify how quickly adoption of AI technology occurs and how long it takes to affect the labor market. Future work is also needed to tease out the mechanisms that link AI to higher wages, on average and for high-income occupations. We believe the role of specific skills and abilities used in occupations is an important piece to the puzzle.

Our results provide broad evidence that AI may complement rather than substitute for human labor, at least in the short run. Future work can continue to investigate how the impact of AI manifests across occupations, geographies, and backgrounds. For example, other research has described conditions under which AI may exacerbate existing trends in inequality and pose significant challenges to labor reskilling (Acemoglu and Restrepo 2018, Korinek and Stiglitz 2018). The AIOI generated by our methodology could be used to study heterogeneity of impact across educational backgrounds, income levels, and other demographics. It is our hope that our methods and results can be a useful tool for scholars, policymakers, and practitioners in predicting the effects of AI on different occupations.

AI technologies are rapidly advancing and are expected to have dramatic effects on the economy. Our results indicate that we must be careful when talking about the impact of AI as a monolithic, primarily negative force, and that there is significant nuance in understanding and interpreting its effect on the labor market. While much work must still be done to examine the relationship between AI and labor, we believe our study contributes to the nascent and growing body of literature examining this important topic.

References

Acemoglu D, Autor D (2011) Skills, Tasks and Technologies: Implications for Employment and Earnings. *Handbook of Labor Economics*. (Elsevier), 1043–1171.

Acemoglu D, Restrepo P (2018) Robots and Jobs: Evidence from US Labor Markets. *Working Paper*:90.

Agarwal R, Dhar V (2014) Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research. *Information Systems Research* 25(3):443–448.

Agrawal A, Gans J, Goldfarb A (2017) How AI Could Change Amazon: A Thought Experiment. *Harvard Business Review* (October 3) https://hbr.org/2017/10/how-ai-could-change-amazon-a-thought-experiment.

Agrawal A, Gans JS, Goldfarb A (2019) *Artificial Intelligence: The Ambiguous Labor Market Impact of Automating Prediction* (Social Science Research Network, Rochester, NY).

Anon (2019) AI Progress Measurement. *Electronic Frontier Foundation*. Retrieved (July 11, 2019), https://www.eff.org/ai/metrics.

Anon (2019) O*NET® Database Releases Archive at O*NET Resource Center. Retrieved (July 11, 2019), https://www.onetcenter.org/db_releases.html.

Anon (2019) O*NET Online. Retrieved (February 20, 2019), https://www.onetonline.org/.

Aral S, Brynjolfsson E, Wu L (2012) Three-Way Complementarities: Performance Pay, Human Resource Analytics, and Information Technology. *Management Science* 58(5):913–931.

Autor D, Handel MJ (2013) Putting Tasks to the Test: Human Capital, Job Tasks, and Wages. *Journal of Labor Economics* 31(S1):S59–S96.

Autor DH (2015) Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives* 29(3):3–30.

Autor DH, Dorn D (2013) The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review* 103(5):1553–1597.

Autor DH, Levy F, Murnane RJ (2003) The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics* 118(4):1279–1333.

Avgar A, Tambe P, Hitt L (2018) Built to Learn: How Work Practices Affect Employee Learning During Healthcare Information Technology Implementation. *Management Information Systems Quarterly* 42(2):645–659.

Becker GS (1962) Investment in Human Capital: A Theoretical Analysis. *Journal of Political Economy* 70(5):9–49.

Becker GS (1993) *Human capital: a theoretical and empirical analysis, with special reference to education* 3rd ed. (The University of Chicago Press, Chicago).

Berman E, Bound J, Machin S (1998) Implications of Skill-Biased Technological Change: International Evidence. *Q J Econ* 113(4):1245–1279.

Bessen JE, Goos M, Salomons A, Van den Berge W (2019) *Automatic Reaction - What Happens to Workers at Firms that Automate?* (Social Science Research Network, Rochester, NY).

Brynjolfsson E, McAfee A (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies* (W. W. Norton & Company).

Brynjolfsson E, McAfee A (2017) The Business of Artificial Intelligence. *Harvard Business Review* (July 18) https://hbr.org/2017/07/the-business-of-artificial-intelligence.

Brynjolfsson E, Mitchell T (2017) What can machine learning do? Workforce implications. *Science* 358(6370):1530–1534.

Brynjolfsson E, Mitchell T, Rock D (2018) What Can Machines Learn, and What Does It Mean for Occupations and the Economy? *AEA Papers and Proceedings* 108:43–47.

Brynjolfsson E, Rock D, Syverson C (2017) *Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics* (National Bureau of Economic Research).

Buchanan BG (2005) A (Very) Brief History of Artificial Intelligence. *1* 26(4):53–53.

Card D (1999) The Causal Effect of Education on Earnings. *Handbook of Labor Economics*. (Elsevier), 1801–1863.

Card D, DiNardo JE (2002) Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of Labor Economics* 20(4):733–783.

Choudhury P, Starr E, Agarwal R (2019) Machine Learning and Human Capital: Experimental Evidence on Productivity Complementarities. *SSRN Electronic Journal*.

Council of Economic Advisers (2016) *Economic Report of the President* (Council of Economic Advisors).

Cowgill B (2019) Bias and Productivity in Humans and Machines. *Working Paper*:30.

Dixon J, Hong B, Wu L (2019) *The Employment Consequences of Robots: Firm-Level Evidence* (Social Science Research Network, Rochester, NY).

Dranove D, Forman C, Goldfarb A, Greenstein S (2014) The Trillion Dollar Conundrum: Complementarities and Health Information Technology. *American Economic Journal: Economic Policy* 6(4):239–270.

Eckert F, Ganapati S, Walsh C (2019) Skilled Tradable Services: The Transformation of U.S. High-Skill Labor Markets⇜. *Working Paper*.

Farronata C, Larsen B, Brynjolfsson E (2019) Consumer Protection in an Online World: When Does Occupational Licensing Matter? *Working Paper*.

Felten EW, Raj M, Seamans R (2018) A Method to Link Advances in Artificial Intelligence to Occupational Abilities. *AEA Papers and Proceedings* 108:54–57.

Fossen FM, Sorgner A (2019a) *New Digital Technologies and Heterogeneous Employment and Wage Dynamics in the United States: Evidence from Individual-Level Data* (IZA - Institute for Labor Economics).

Fossen FM, Sorgner A (2019b) The Effects of Digitalization of Work on Entry into Entrepreneurship. *Proceedings* 2019(1):11095.

Frey CB, Osborne MA (2017) The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change* 114:254–280.

Furman J, Seamans R (2019) AI and the Economy. *Innovation Policy and the Economy, Volume 19*:161–191.

Gibbons R, Waldman M (2004) Task-Specific Human Capital. *American Economic Review* 94(2):203–207.

Goldfarb A, Taska B, Teodoridis F (2019) Machine Learning in Healthcare? *Working Paper*.

Goos M, Manning A, Salomons A (2009) Job Polarization in Europe. *American Economic Review* 99(2):58–63.

Goos M, Manning A, Salomons A (2014) Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *American Economic Review* 104(8):2509–2526.

Graetz G, Michaels G (2018) Robots at Work. *The Review of Economics and Statistics*.

Horton JJ, Rand DG, Zeckhauser RJ (2011) The online laboratory: conducting experiments in a real labor market. *Exp Econ* 14(3):399–425.

Hosny A, Parmar C, Quackenbush J, Schwartz LH, Aerts HJWL (2018) Artificial intelligence in radiology. *Nat Rev Cancer* 18(8):500–510.

Hoynes HW, Rothstein J (2019) *Universal Basic Income in the US and Advanced Countries* (National Bureau of Economic Research).
Jha S, Topol EJ (2016) Adapting to Artificial Intelligence: Radiologists and Pathologists as Information Specialists. *JAMA* 316(22):2353–2354.
Kim H, Luca M (2019) Product Quality and Entering Through Tying: Experimental Evidence. *Management Science* 65(2):596–603.
Kleiner MM, Krueger AB (2010) The Prevalence and Effects of Occupational Licensing. *British Journal of Industrial Relations* 48(4):676–687.
Korinek A, Stiglitz JE (2018) Artificial Intelligence and Its Implications for Income Distribution and Unemployment. *NBER Chapters*. (National Bureau of Economic Research, Inc), 349–390.
Levy S (2018) How Amazon Rebuilt Itself Around Artificial Intelligence. *Wired* (February 1) https://www.wired.com/story/amazon-artificial-intelligence-flywheel/.
McElheran K (2018) Economic Measurement of AI. *Working Paper*:29.
Menzies T (2003) 21st-century AI: proud, not smug. *IEEE Intelligent Systems* 18(3):18–24.
Mishel L, Shierholz H, Schmitt J (2013) *Don't Blame the Robots: Assessing the Job Polarization Explanation of Growing Wage Inequality* (Economic Policy Institute).
Mochizuki T (2019) How Gaming Technology May Help Taxi Drivers in Japan. *Wall Street Journal* (April 1) https://www.wsj.com/articles/how-gaming-technology-may-help-taxi-drivers-in-japan-11554155261.
Mokyr J, Vickers C, Ziebarth NL (2015) The History of Technological Anxiety and the Future of Economic Growth: Is This Time Different? *Journal of Economic Perspectives* 29(3):31–50.
Murphy F (2017) Truck drivers like me will soon be replaced by automation. You're next | Finn Murphy. *The Guardian* (November 17) https://www.theguardian.com/commentisfree/2017/nov/17/truck-drivers-automation-tesla-elon-musk.
Norvig P, Russell SJ (1994) *Artificial Intelligence: A Modern Approach* (Prentice Hall, Pearson, NJ).
O'Brien M (2019) Chefs and Truck Drivers Beware: AI Is Coming for Your Jobs. *US News & World Report*. Retrieved (July 12, 2019), https://www.usnews.com/news/business/articles/2019-01-24/chefs-and-truck-drivers-beware-ai-is-coming-for-your-jobs.
Pakdemirli E (2019) Artificial intelligence in radiology: friend or foe? Where are we now and where are we heading? *Acta Radiol Open* 8(2).
Raj M, Seamans R (2018) *AI, Labor, Productivity and the Need for Firm-Level Data* (National Bureau of Economic Research, Cambridge, MA).
Raj M, Seamans R (2019) Primer on artificial intelligence and robotics. *Journal of Organization Design* 8(1):1–14.
Rea B, Stachura S, Wallace L, Pankratz DM (2017) *How the new transportation ecosystem is reshaping the future of work* (Deloitte).
Romer PM (1990) Endogenous Technological Change. *Journal of Political Economy* 98(5):S71–S102.
Solow RM (1957) Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics* 39(3):312–320.

Tambe P (2014) Big Data Investment, Skills, and Firm Value. *Management Science* 60(6):1452–1469.
Tambe P, Hitt LM (2014) Job Hopping, Information Technology Spillovers, and Productivity Growth. *Management Science* 60(2):338–355.
Tangermann V (2019) Amazon used an AI to automatically fire low-productivity workers. *Futurism*. Retrieved (August 7, 2019), https://futurism.com/amazon-ai-fire-workers.
Vanian J (2017) In 10 Years, Artificial Intelligence Will Transform Trucking, Says Otto Exec. *Fortune*. Retrieved (July 12, 2019), https://fortune.com/2017/03/27/uber-otto-artificial-intelligence-truck-driving/.

Table 1: EFF Application Definitions and Calculated Rates of Progress

AI Application	Definition	Rate of Progress (2010-2015)
Abstract Strategy Games	The ability to play abstract games involving sometimes complex strategy and reasoning ability, such as Chess, Go, or Checkers, at a high level.	0.0180
Real-Time Video Games	The ability to play a variety of real-time video games of increasing complexity at a high level.	0.2710
Image Recognition	The determination of what objects are present in a still image.	0.2300
Visual Question Answering	The recognition of events, relationships, and context from a still image.	0.1490
Image Generation	The creation of complex images.	0.0925
Reading Comprehension	The ability to answer simple reasoning question based on an understanding of text.	0.1890
Language Modeling	The ability to model, predict, or mimic human language.	0.0127
Translation	The translation of words or text from one language into another.	0.0091
Speech Recognition	The recognition of spoken language into text.	0.0810

Note: To calculate the rate of progress within each application, we first scale each metric to account for the exponential rate of progress using the negative logarithm of the metric. Within an application, we then calculate the rate of progress by fitting a linear model across the scaled metrics along with a per-metric offset.

Table 2: Occupations with the Highest and Lowest AIOI Score (2010 – 2015)

Rank	Highest Scoring	Lowest Scoring
1	Civil Engineers	Dancers
2	Financial Examiners	Fitness Trainers and Aerobics Instructors
3	Actuaries	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons
4	Mechanical Engineers	Brickmasons and Blockmasons
5	Budget Analysts	Dining Room and Cafeteria Attendants and Bartender Helpers
6	Chemical Engineers	Athletes and Sports Competitors
7	Cartographers and Photogrammetrists	Packers and Packagers, Hand
8	Statisticians	Helpers--Roofers
9	Astronomers	Massage Therapists
10	Atmospheric and Space Scientists	Choreographers
11	Accountants and Auditors	Slaughterers and Meat Packers
12	Epidemiologists	Dishwashers
13	Mathematicians	Fence Erectors
14	Computer Programmers	Reinforcing Iron and Rebar Workers
15	Operations Research Analysts	Pressers, Textile, Garment, and Related Materials
16	Credit Analysts	Baggage Porters and Bellhops
17	Nuclear Engineers	Painters, Construction and Maintenance
18	Cost Estimators	Maids and Housekeeping Cleaners
19	Geoscientists, Except Hydrologists and Geographers	Roofers
20	Computer Software Engineers, Applications	Stonemasons

Note: Occupations are ranked by their constructed AIOI Score from 2010 to 2015 at the six-digit Standard Occupational Classification (SOC) level. See draft for a detailed description of the construction of the AIOI Score. Occupation titles are taken from the O*NET database. Highest-scoring occupations are ranked in descending order based on the AIOI Score. Lowest scoring occupations are ranked in ascending order based on the AIOI Score.

Table 3: Correlation Coefficients across mTurk Subsamples by EFF AI Application

	Correlation Coefficient between Subsample and the Full Sample	
EFF AI Application	**Graduate Students**	**Computer Science or Engineering Backgrounds**
Abstract Strategy Games	0.97	0.92
Real-Time Video Games	0.96	0.87
Image Recognition	0.97	0.94
Visual Question Answering	0.98	0.90
Generating Images	0.98	0.94
Reading Comprehension	0.99	0.95
Language Modeling	0.99	0.96
Translation	0.99	0.95
Speech Recognition	0.99	0.94
Instrumental Track Recognition	0.98	0.94

Note: Correlation coefficients are calculated for the vectors of responses of the different subsamples listed in the mTurk survey used to construct the matrix connecting Electronic Frontier Foundation (EFF) AI application with O*NET abilities.

Table 4: Correlation Coefficients across mTurk Subsamples by O*NET Ability

O*NET Abilities	Correlation Coefficient between Subsample and the Full Sample: Graduate Students	Computer Science or Engineering Backgrounds
Arm-Hand Steadiness	0.97	0.92
Auditory Attention	0.98	0.93
Category Flexibility	0.87	0.91
Control Precision	0.97	0.98
Deductive Reasoning	0.89	0.94
Depth Perception	0.98	0.99
Dynamic Flexibility	0.91	0.95
Dynamic Strength	0.79	0.86
Explosive Strength	0.87	0.86
Extent Flexibility	0.91	0.91
Far Vision	0.98	0.95
Finger Dexterity	0.97	0.97
Flexibility of Closure	0.92	0.87
Fluency of Ideas	0.92	0.91
Glare Sensitivity	0.99	0.97
Gross Body Coordination	0.94	0.96
Gross Body Equilibrium	0.91	0.85
Hearing Sensitivity	0.99	0.91
Inductive Reasoning	0.79	0.80
Information Ordering	0.85	0.84
Manual Dexterity	0.97	0.98
Mathematical Reasoning	0.97	0.87
Memorization	0.88	0.72
Multilimb Coordination	0.98	0.93
Near Vision	0.99	0.95
Night Vision	0.97	0.96
Number Facility	0.99	0.90
Oral Comprehension	0.99	0.95
Oral Expression	0.96	0.87
Originality	0.91	0.84
Perceptual Speed	0.96	0.91
Peripheral Vision	0.98	0.96
Problem Sensitivity	0.89	0.95
Rate Control	0.98	0.98
Reaction Time	0.97	0.90
Response Orientation	0.98	0.92
Selective Attention	0.96	0.62
Sound Localization	0.97	0.97
Spatial Orientation	0.99	0.97
Speech Clarity	0.96	0.83
Speech Recognition	0.99	0.92
Speed of Closure	0.91	0.91
Speed of Limb Movement	0.97	0.93
Stamina	0.94	0.84
Static Strength	0.89	0.81
Time Sharing	0.95	0.91
Trunk Strength	0.88	0.72
Visual Color Determination	0.99	0.98
Visualization	0.99	0.96
Wrist-Finger Speed	0.98	0.94
Written Comprehension	0.96	0.93
Written Expression	0.98	0.89

Note: Correlation coefficients are calculated for the vectors of responses of the different subsamples listed in the mTurk survey used to construct the matrix connecting Electronic Frontier Foundation (EFF) AI applications with O*NET abilities.

Table 5: OLS Estimate of the Relationship between AIOI and the Change in Occupation-Level AI Skills

	(1) Change in AI Skills (2010 - 2016)	(2) Change in AI Skills (2010 - 2016)
AIOI Score	0.024***	0.016***
	(0.005)	(0.004)
Degree of Automation		0.000**
		(0.000)
Importance of Programming		0.000115***
		0.000
Constant	-0.015***	-0.012***
	(0.003)	(0.002)
Observations	700	691
R-squared	0.052	0.157

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Ordinary least squares estimates with robust Huber-White standard errors. Change in AI Skills is measured as the average change in the count of AI skills required at the occupation-level calculated using Burning Glass Labor Insight Data. AI Skills are classified as skills within the Burning Glass Skill Clusters of “Artificial Intelligence”, “Machine Learning”, and “Natural Language Processing.” Change in AI Skills is winsorized at the 1st percentile and 99th percentile of the distribution. All variables relying on information from O*NET rely upon the O*NET data as of December 2009. See draft for a detailed description of the construction of the AIOI Score and the set of control variables used.

Table 6: Descriptive Statistics

Variable	Source	Mean	Standard Deviation	Minimum	Maximum
AIOI Score	Authors' Calculations	0.67	0.04	0.56	0.73
Employment Growth (2010-2016)	BLS	17.1%	70.5%	-96.4%	1850.0%
Median Wage Growth (2010-2016)	BLS	11.8%	17.5%	-83.0%	280.3%
Employment Growth (2005-2010)	BLS	8.3%	72.7%	-95.3%	4366.7%
Median Wage Growth (2005-2010)	BLS	16.2%	17.9%	-67.0%	267.6%
Degree of Automation	O*NET	43.78	11.13	20.80	79.40
Importance of Programming	O*NET	33.36	11.33	20.00	99.00
Proportion of Software Skills	Burning Glass	6.3%	6.7%	0.0%	56.7%
State Population Change	FRED	4.2%	3.4%	-1.4%	13.1%

Note: Statistics are calculated for all occupations for which data are available for the given variable. Employment and wage growth are calculated at the state-occupation level for all occupations for which there is employment and wage data in both 2010 and 2016. All variables relying on information from O*NET, including the AI Occupation Impact Score, rely upon the O*NET data as of December 2009. All variables derived from the Burning Glass data rely on occupation data from 2010. See draft for a detailed description of the construction of the AIOI Score and the set of control variables used.

Table 7: Relationship between AIOI and Employment and Wage Growth (2010 – 2016)

	Employment Growth (2010-2016)				Wage Growth (2010-2016)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AIOI Score	-0.0254	-0.0292	-0.0463	0.1231	0.1367***	0.1345***	0.1311***	0.1160***
	(0.1409)	(0.1432)	(0.1458)	(0.1512)	(0.0367)	(0.0368)	(0.0367)	(0.0402)
Employment Growth (2005-2010)	-0.1443***	-0.1472***	-0.1468***	-0.1485***				
	(0.0122)	(0.0122)	(0.0124)	(0.0125)				
Wage Growth (2005-2010)					-0.3349***	-0.3364***	-0.3458***	-0.3505***
					(0.0129)	(0.0125)	(0.0126)	(0.0129)
Degree of Automation				-0.0035***				-0.0000
				(0.0003)				(0.0001)
Importance of Programming				0.0021***				0.0003***
				(0.0004)				(0.0001)
State Population Change (2010-2016)		1.2400***				0.1944		
		(0.2185)				(0.1495)		
Constant	0.1840*	0.1359	0.1983**	0.1160	0.0772***	0.0709***	0.0827***	0.0843***
	(0.0962)	(0.0968)	(0.0980)	(0.0990)	(0.0261)	(0.0257)	(0.0247)	(0.0256)
State FEs	No	No	Yes	Yes	No	No	Yes	Yes
Observations	25,485	25,485	25,485	25,143	27,899	27,899	27,899	27,497
R-squared	0.0191	0.0233	0.0288	0.0342	0.0003	0.0010	0.0177	0.0196

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: Ordinary least squares estimates with standard errors clustered at the state level. Employment and wage growth are calculated for all occupations for which there is employment and wage data in both 2010 and 2016. Employment growth is the percent change in total employment. Wage growth is calculated as the percent change in median wage. Occupations with missing values for any data are dropped from the analysis. All variables relying on information from O*NET rely upon the O*NET data as of December 2009. See draft for a detailed description of the construction of the AIOI Score and the set of control variables used.

Table 8: Relationship between AIOI and Employment and Wage Growth (2010 – 2016) by Prevalence of Software Skills

	Employment Growth (2010-2016)			Wage Growth (2010-2016)		
	Low Software Prevalence	Medium Software Prevalence	High Software Prevalence	Low Software Prevalence	Medium Software Prevalence	High Software Prevalence
	(1)	(2)	(3)	(4)	(5)	(6)
AIOI Score	0.3896	-0.0287	0.3215	0.0620	-0.0513	0.1746***
	(0.2331)	(0.2710)	(0.2581)	(0.0729)	(0.0626)	(0.0558)
Employment Growth (2005-2010)	-0.1580***	-0.1573***	-0.1332***			
	(0.0197)	(0.0171)	(0.0229)			
Wage Growth (2005-2010)				-0.3443***	-0.3730***	-0.3325***
				(0.0185)	(0.0162)	(0.0235)
Degree of Automation	-0.0026***	-0.0020***	-0.0055***	-0.0003**	-0.0002	0.0001
	(0.0004)	(0.0006)	(0.0007)	(0.0001)	(0.0002)	(0.0002)
Importance of Programming	-0.0024***	0.0009	0.0049***	0.0005***	0.0004*	0.0002
	(0.0007)	(0.0009)	(0.0006)	(0.0002)	(0.0002)	(0.0001)
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,967	8,251	7,906	9,168	8,762	8,201
R-squared	0.0469	0.0355	0.0474	0.1685	0.1616	0.1389

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Ordinary least squares estimates with standard errors clustered at the state level. Employment and wage growth are calculated for all occupations for which there is employment and wage data in both 2010 and 2016. Employment growth is the percent change in total employment. Wage growth is calculated as the percent change in median wage. Occupations with missing values for any data are dropped from the analysis. All variables relying on information from O*NET rely upon the O*NET data as of December 2009. All variables derived from the Burning Glass data from 2010. Occupations are classified as low, medium, or high automation based on which tercile the proportion of software skills score, constructed using Burning Glass data, falls in. Standard errors are clustered at the state level. See draft for a detailed description of the construction of the AI Occupation Impact Score and the set of control variables used.

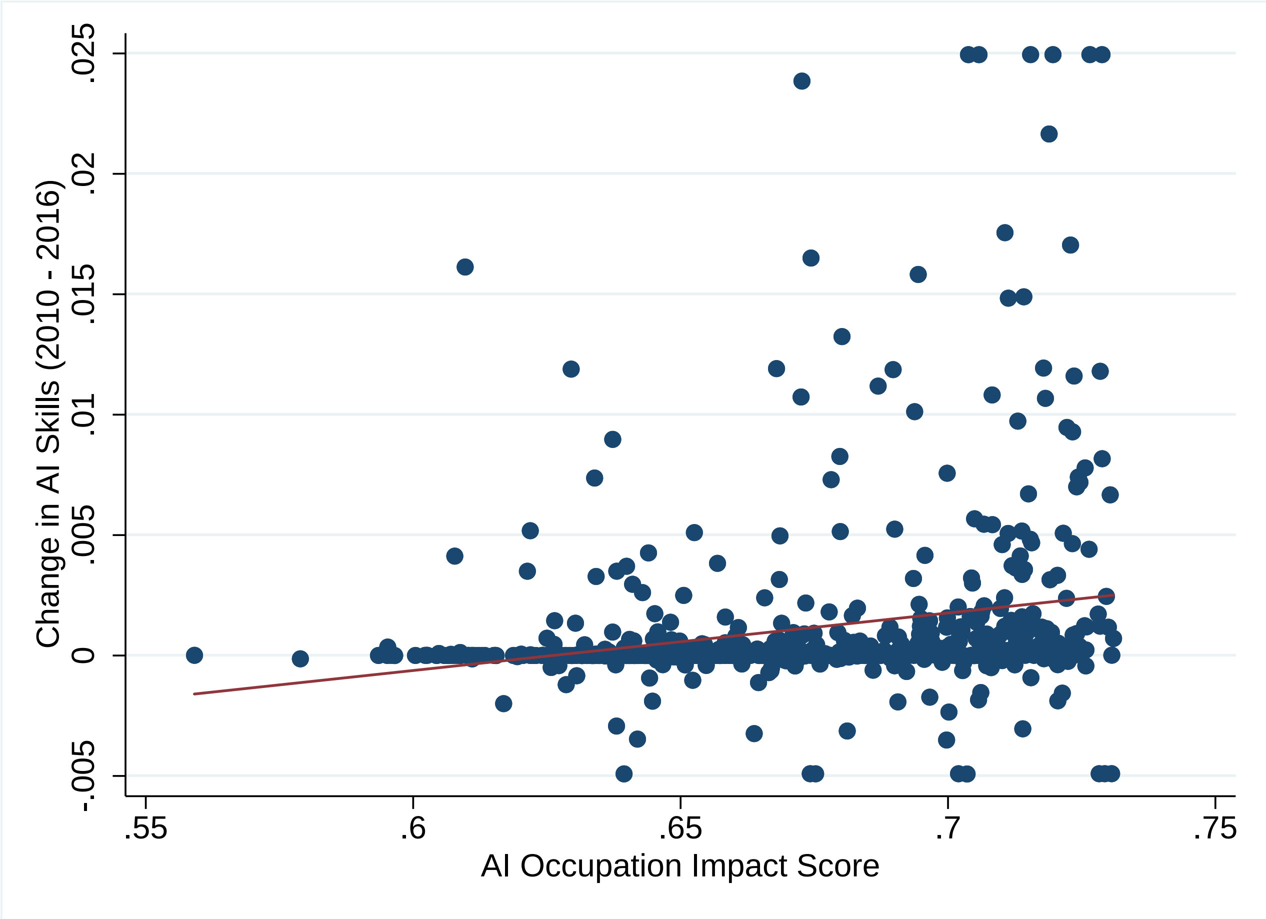
Table 9: Relationship between AIOI and Employment and Wage Growth (2010 – 2016) by Income Tercile

	Employment Growth (2010-2016)			Wage Growth (2010-2016)		
	Low Income	Middle Income	High Income	Low Income	Middle Income	High Income
	(1)	(2)	(3)	(4)	(5)	(6)
AIOI Score	-0.2757	-0.1935	0.9861***	0.0044	0.0856	0.3494***
	(0.2169)	(0.2513)	(0.2343)	(0.0454)	(0.0532)	(0.0753)
Employment Growth (2005-2010)	-0.1787***	-0.1341***	-0.1421***			
	(0.0167)	(0.0197)	(0.0157)			
Wage Growth (2005-2010)				-0.3952***	-0.3426***	-0.3257***
				(0.0137)	(0.0145)	(0.0272)
Degree of Automation	-0.0063***	-0.0022***	-0.0008	-0.0001	-0.0001	0.0003
	(0.0005)	(0.0006)	(0.0005)	(0.0001)	(0.0002)	(0.0002)
Importance of Programming	0.0031***	0.0014*	0.0019***	0.0001	0.0007***	0.0001
	(0.0010)	(0.0007)	(0.0006)	(0.0002)	(0.0002)	(0.0001)
State FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,829	8,220	7,891	9,475	8,734	7,942
R-squared	0.0502	0.0351	0.0425	0.1985	0.1544	0.1326

Clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Ordinary least squares estimates with standard errors clustered at the state level. Employment and wage growth are calculated for all occupations for which there is employment and wage data in both 2010 and 2016. Employment growth is the percent change in total employment. Wage growth is calculated as the percent change in median wage. Occupations with missing values for any data are dropped from the analysis. All variables relying on information from O*NET rely upon the O*NET data as of December 2009. All variables derived from the Burning Glass data from 2010. Occupations are classified as low, middle, or high income based on the occupation's annual income in 2010 based on the data from the Bureau of Labor Statistics. Standard errors are clustered at the state level. See draft for a detailed description of the construction of the AI Occupation Impact Score and the set of control variables used.

Figure 1: Scatterplot of AIOI Score and Change in AI Skills (2010 – 2016)



Note: Change in AI Skills is measured as the average change in the count of AI skills required at the occupation level calculated using Burning Glass Labor Insight Data. AI Skills are classified as skills within the Burning Glass Skill Clusters of "Artificial Intelligence," "Machine Learning," and "Natural Language Processing." Change in AI Skills is winsorized at the 1st percentile and 99th percentile of the distribution. See draft for a detailed description of the construction of the AIOI Score.

Online Appendix for

The Occupational Impact of Artificial Intelligence: Labor, Skills, and Polarization

Appendix Figure A1: MTurk Survey Question

Appendix B: AI Impact Scores by Occupation

Figure A1: MTurk Survey Question

Artificial intelligence in terms of image recognition is defined as the determination of what objects are present in a still picture. For the following human abilities defined below, please answer "Yes" or "No" depending on whether you believe that image recognition by a computer or machine is related to or could be used for each ability.

Peripheral Vision: The ability to see objects or movement of objects to one's side when the eyes are looking ahead.

Do you believe that image recognition by a computer or machine could be used for peripheral vision?

- ○ Yes
- ○ No

Appendix B: AIOI Scores by Occupation Based on December 2009 O*NET Occupational Definitions

SOC Code	Occupation Title	AI Impact Score
11-1011	Chief Executives	0.719
11-1021	General and Operations Managers	0.683
11-2011	Advertising and Promotions Managers	0.715
11-2021	Marketing Managers	0.724
11-2022	Sales Managers	0.706
11-2031	Public Relations Managers	0.714
11-3011	Administrative Services Managers	0.715
11-3021	Computer and Information Systems Managers	0.711
11-3031	Financial Managers	0.723
11-3040	Human Resources Managers	0.721
11-3041	Compensation and Benefits Managers	0.719
11-3042	Training and Development Managers	0.709
11-3051	Industrial Production Managers	0.691
11-3061	Purchasing Managers	0.721
11-3071	Transportation, Storage, and Distribution Managers	0.700
11-9011	Farm, Ranch, and Other Agricultural Managers	0.687
11-9012	Farmers and Ranchers	0.648
11-9021	Construction Managers	0.718
11-9031	Education Administrators, Preschool and Child Care Center/Program	0.680
11-9032	Education Administrators, Elementary and Secondary School	0.695
11-9033	Education Administrators, Postsecondary	0.715
11-9041	Engineering Managers	0.723
11-9051	Food Service Managers	0.669
11-9061	Funeral Directors	0.666
11-9071	Gaming Managers	0.690
11-9081	Lodging Managers	0.709
11-9111	Medical and Health Services Managers	0.685
11-9121	Natural Sciences Managers	0.708
11-9131	Postmasters and Mail Superintendents	0.709
11-9141	Property, Real Estate, and Community Association Managers	0.717
11-9151	Social and Community Service Managers	0.701
11-9199	Managers, All Other	0.722
13-1011	Agents and Business Managers of Artists, Performers, and Athletes	0.706
13-1021	Purchasing Agents and Buyers, Farm Products	0.687
13-1022	Wholesale and Retail Buyers, Except Farm Products	0.691
13-1023	Purchasing Agents, Except Wholesale, Retail, and Farm Products	0.724
13-1031	Claims Adjusters, Examiners, and Investigators	0.723
13-1032	Insurance Appraisers, Auto Damage	0.716

13-1041	Compliance Officers, Except Agriculture, Construction, Health and Safety, and Transportation	0.697
13-1051	Cost Estimators	0.726
13-1061	Emergency Management Specialists	0.720
13-1071	Employment, Recruitment, and Placement Specialists	0.715
13-1072	Compensation, Benefits, and Job Analysis Specialists	0.721
13-1073	Training and Development Specialists	0.710
13-1081	Logisticians	0.724
13-1111	Management Analysts	0.722
13-1121	Meeting and Convention Planners	0.672
13-1199	Business Operations Specialists, All Other	0.669
13-2011	Accountants and Auditors	0.728
13-2021	Appraisers and Assessors of Real Estate	0.701
13-2031	Budget Analysts	0.730
13-2041	Credit Analysts	0.726
13-2051	Financial Analysts	0.726
13-2052	Personal Financial Advisors	0.718
13-2053	Insurance Underwriters	0.721
13-2061	Financial Examiners	0.731
13-2071	Loan Counselors	0.724
13-2072	Loan Officers	0.718
13-2081	Tax Examiners, Collectors, and Revenue Agents	0.724
13-2082	Tax Preparers	0.723
15-1011	Computer and Information Scientists, Research	0.719
15-1021	Computer Programmers	0.727
15-1031	Computer Software Engineers, Applications	0.726
15-1032	Computer Software Engineers, Systems Software	0.716
15-1041	Computer Support Specialists	0.683
15-1051	Computer Systems Analysts	0.721
15-1061	Database Administrators	0.724
15-1071	Network and Computer Systems Administrators	0.715
15-1081	Network Systems and Data Communications Analysts	0.719
15-1099	Computer Specialists, All Other	0.718
15-2011	Actuaries	0.731
15-2021	Mathematicians	0.728
15-2031	Operations Research Analysts	0.727
15-2041	Statisticians	0.729
15-2091	Mathematical Technicians	0.708
17-1011	Architects, Except Landscape and Naval	0.722
17-1012	Landscape Architects	0.714
17-1021	Cartographers and Photogrammetrists	0.729
17-1022	Surveyors	0.674
17-2011	Aerospace Engineers	0.724

17-2021	Agricultural Engineers	0.711
17-2031	Biomedical Engineers	0.680
17-2041	Chemical Engineers	0.730
17-2051	Civil Engineers	0.731
17-2061	Computer Hardware Engineers	0.715
17-2071	Electrical Engineers	0.715
17-2072	Electronics Engineers, Except Computer	0.710
17-2081	Environmental Engineers	0.725
17-2111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	0.719
17-2112	Industrial Engineers	0.712
17-2121	Marine Engineers and Naval Architects	0.693
17-2131	Materials Engineers	0.713
17-2141	Mechanical Engineers	0.730
17-2151	Mining and Geological Engineers, Including Mining Safety Engineers	0.700
17-2161	Nuclear Engineers	0.726
17-2171	Petroleum Engineers	0.722
17-2199	Engineers, All Other	0.708
17-3011	Architectural and Civil Drafters	0.714
17-3012	Electrical and Electronics Drafters	0.715
17-3013	Mechanical Drafters	0.720
17-3021	Aerospace Engineering and Operations Technicians	0.691
17-3022	Civil Engineering Technicians	0.718
17-3023	Electrical and Electronic Engineering Technicians	0.696
17-3024	Electro-Mechanical Technicians	0.678
17-3025	Environmental Engineering Technicians	0.680
17-3026	Industrial Engineering Technicians	0.710
17-3027	Mechanical Engineering Technicians	0.667
17-3029	Engineering Technicians, Except Drafters, All Other	0.678
17-3031	Surveying and Mapping Technicians	0.686
19-1011	Animal Scientists	0.718
19-1012	Food Scientists and Technologists	0.696
19-1013	Soil and Plant Scientists	0.694
19-1020	Biologists	0.721
19-1021	Biochemists and Biophysicists	0.705
19-1022	Microbiologists	0.706
19-1023	Zoologists and Wildlife Biologists	0.700
19-1031	Conservation Scientists	0.675
19-1032	Foresters	0.669
19-1041	Epidemiologists	0.728
19-1042	Medical Scientists, Except Epidemiologists	0.718
19-2011	Astronomers	0.729
19-2012	Physicists	0.726
19-2021	Atmospheric and Space Scientists	0.728

19-2031	Chemists	0.695
19-2032	Materials Scientists	0.713
19-2041	Environmental Scientists and Specialists, Including Health	0.714
19-2042	Geoscientists, Except Hydrologists and Geographers	0.726
19-2043	Hydrologists	0.725
19-2099	Physical Scientists, All Other	0.720
19-3011	Economists	0.718
19-3021	Market Research Analysts	0.725
19-3022	Survey Researchers	0.720
19-3031	Clinical, Counseling, and School Psychologists	0.718
19-3032	Industrial-Organizational Psychologists	0.722
19-3041	Sociologists	0.713
19-3051	Urban and Regional Planners	0.720
19-3091	Anthropologists and Archeologists	0.697
19-3092	Geographers	0.723
19-3093	Historians	0.694
19-3094	Political Scientists	0.716
19-4011	Agricultural and Food Science Technicians	0.682
19-4021	Biological Technicians	0.691
19-4031	Chemical Technicians	0.674
19-4041	Geological and Petroleum Technicians	0.680
19-4051	Nuclear Technicians	0.675
19-4061	Social Science Research Assistants	0.719
19-4091	Environmental Science and Protection Technicians, Including Health	0.676
19-4092	Forensic Science Technicians	0.690
19-4093	Forest and Conservation Technicians	0.657
19-4099	Life, Physical, and Social Science Technicians, All Other	0.681
21-1011	Substance Abuse and Behavioral Disorder Counselors	0.702
21-1012	Educational, Vocational, and School Counselors	0.707
21-1013	Marriage and Family Therapists	0.721
21-1014	Mental Health Counselors	0.712
21-1015	Rehabilitation Counselors	0.676
21-1021	Child, Family, and School Social Workers	0.691
21-1022	Medical and Public Health Social Workers	0.698
21-1023	Mental Health and Substance Abuse Social Workers	0.706
21-1091	Health Educators	0.692
21-1092	Probation Officers and Correctional Treatment Specialists	0.676
21-1093	Social and Human Service Assistants	0.681
21-2011	Clergy	0.705
21-2021	Directors, Religious Activities and Education	0.699
23-1011	Lawyers	0.718
23-1021	Administrative Law Judges, Adjudicators, and Hearing Officers	0.720
23-1022	Arbitrators, Mediators, and Conciliators	0.715

23-1023	Judges, Magistrate Judges, and Magistrates	0.718
23-2011	Paralegals and Legal Assistants	0.723
23-2091	Court Reporters	0.695
23-2092	Law Clerks	0.725
23-2093	Title Examiners, Abstractors, and Searchers	0.720
25-1011	Business Teachers, Postsecondary	0.713
25-1021	Computer Science Teachers, Postsecondary	0.704
25-1022	Mathematical Science Teachers, Postsecondary	0.714
25-1031	Architecture Teachers, Postsecondary	0.708
25-1032	Engineering Teachers, Postsecondary	0.716
25-1041	Agricultural Sciences Teachers, Postsecondary	0.702
25-1042	Biological Science Teachers, Postsecondary	0.700
25-1043	Forestry and Conservation Science Teachers, Postsecondary	0.706
25-1051	Atmospheric, Earth, Marine, and Space Sciences Teachers, Postsecondary	0.716
25-1052	Chemistry Teachers, Postsecondary	0.705
25-1053	Environmental Science Teachers, Postsecondary	0.714
25-1054	Physics Teachers, Postsecondary	0.707
25-1061	Anthropology and Archeology Teachers, Postsecondary	0.718
25-1062	Area, Ethnic, and Cultural Studies Teachers, Postsecondary	0.710
25-1063	Economics Teachers, Postsecondary	0.714
25-1064	Geography Teachers, Postsecondary	0.705
25-1065	Political Science Teachers, Postsecondary	0.702
25-1066	Psychology Teachers, Postsecondary	0.705
25-1067	Sociology Teachers, Postsecondary	0.705
25-1071	Health Specialties Teachers, Postsecondary	0.714
25-1072	Nursing Instructors and Teachers, Postsecondary	0.697
25-1081	Education Teachers, Postsecondary	0.700
25-1082	Library Science Teachers, Postsecondary	0.720
25-1111	Criminal Justice and Law Enforcement Teachers, Postsecondary	0.709
25-1112	Law Teachers, Postsecondary	0.707
25-1113	Social Work Teachers, Postsecondary	0.707
25-1121	Art, Drama, and Music Teachers, Postsecondary	0.689
25-1122	Communications Teachers, Postsecondary	0.703
25-1123	English Language and Literature Teachers, Postsecondary	0.711
25-1124	Foreign Language and Literature Teachers, Postsecondary	0.704
25-1125	History Teachers, Postsecondary	0.709
25-1126	Philosophy and Religion Teachers, Postsecondary	0.704
25-1191	Graduate Teaching Assistants	0.698
25-1192	Home Economics Teachers, Postsecondary	0.713
25-1193	Recreation and Fitness Studies Teachers, Postsecondary	0.686
25-1194	Vocational Education Teachers, Postsecondary	0.672
25-2011	Preschool Teachers, Except Special Education	0.667
25-2012	Kindergarten Teachers, Except Special Education	0.681

25-2021	Elementary School Teachers, Except Special Education	0.681
25-2022	Middle School Teachers, Except Special and Vocational Education	0.684
25-2023	Vocational Education Teachers, Middle School	0.673
25-2031	Secondary School Teachers, Except Special and Vocational Education	0.679
25-2032	Vocational Education Teachers, Secondary School	0.670
25-2041	Special Education Teachers, Preschool, Kindergarten, and Elementary School	0.684
25-2042	Special Education Teachers, Middle School	0.696
25-2043	Special Education Teachers, Secondary School	0.697
25-3011	Adult Literacy, Remedial Education, and GED Teachers and Instructors	0.709
25-3021	Self-Enrichment Education Teachers	0.668
25-4011	Archivists	0.699
25-4012	Curators	0.681
25-4013	Museum Technicians and Conservators	0.680
25-4021	Librarians	0.714
25-4031	Library Technicians	0.669
25-9011	Audio-Visual Collections Specialists	0.684
25-9021	Farm and Home Management Advisors	0.703
25-9031	Instructional Coordinators	0.710
25-9041	Teacher Assistants	0.695
27-1011	Art Directors	0.713
27-1012	Craft Artists	0.641
27-1013	Fine Artists, Including Painters, Sculptors, and Illustrators	0.658
27-1014	Multi-Media Artists and Animators	0.707
27-1021	Commercial and Industrial Designers	0.714
27-1022	Fashion Designers	0.697
27-1023	Floral Designers	0.675
27-1024	Graphic Designers	0.710
27-1025	Interior Designers	0.720
27-1026	Merchandise Displayers and Window Trimmers	0.619
27-1027	Set and Exhibit Designers	0.666
27-2011	Actors	0.673
27-2012	Producers and Directors	0.702
27-2021	Athletes and Sports Competitors	0.596
27-2022	Coaches and Scouts	0.664
27-2023	Umpires, Referees, and Other Sports Officials	0.680
27-2031	Dancers	0.559
27-2032	Choreographers	0.603
27-2041	Music Directors and Composers	0.696
27-2042	Musicians and Singers	0.658
27-3011	Radio and Television Announcers	0.706
27-3012	Public Address System and Other Announcers	0.679
27-3021	Broadcast News Analysts	0.711
27-3022	Reporters and Correspondents	0.704

27-3031	Public Relations Specialists	0.713
27-3041	Editors	0.720
27-3042	Technical Writers	0.711
27-3043	Writers and Authors	0.706
27-3091	Interpreters and Translators	0.694
27-4011	Audio and Video Equipment Technicians	0.668
27-4012	Broadcast Technicians	0.692
27-4013	Radio Operators	0.701
27-4014	Sound Engineering Technicians	0.668
27-4021	Photographers	0.681
27-4031	Camera Operators, Television, Video, and Motion Picture	0.666
27-4032	Film and Video Editors	0.687
29-1011	Chiropractors	0.653
29-1021	Dentists, General	0.674
29-1022	Oral and Maxillofacial Surgeons	0.658
29-1023	Orthodontists	0.684
29-1024	Prosthodontists	0.665
29-1031	Dietitians and Nutritionists	0.714
29-1041	Optometrists	0.703
29-1051	Pharmacists	0.691
29-1061	Anesthesiologists	0.680
29-1062	Family and General Practitioners	0.707
29-1063	Internists, General	0.708
29-1064	Obstetricians and Gynecologists	0.677
29-1065	Pediatricians, General	0.711
29-1066	Psychiatrists	0.712
29-1067	Surgeons	0.671
29-1071	Physician Assistants	0.681
29-1081	Podiatrists	0.695
29-1111	Registered Nurses	0.661
29-1121	Audiologists	0.700
29-1122	Occupational Therapists	0.662
29-1123	Physical Therapists	0.648
29-1124	Radiation Therapists	0.665
29-1125	Recreational Therapists	0.651
29-1126	Respiratory Therapists	0.667
29-1127	Speech-Language Pathologists	0.700
29-1131	Veterinarians	0.672
29-1199	Health Diagnosing and Treating Practitioners, All Other	0.690
29-2011	Medical and Clinical Laboratory Technologists	0.683
29-2012	Medical and Clinical Laboratory Technicians	0.669
29-2021	Dental Hygienists	0.654
29-2031	Cardiovascular Technologists and Technicians	0.668

29-2032	Diagnostic Medical Sonographers	0.661
29-2033	Nuclear Medicine Technologists	0.670
29-2034	Radiologic Technologists and Technicians	0.648
29-2041	Emergency Medical Technicians and Paramedics	0.647
29-2051	Dietetic Technicians	0.667
29-2052	Pharmacy Technicians	0.675
29-2053	Psychiatric Technicians	0.652
29-2054	Respiratory Therapy Technicians	0.669
29-2055	Surgical Technologists	0.657
29-2056	Veterinary Technologists and Technicians	0.654
29-2061	Licensed Practical and Licensed Vocational Nurses	0.641
29-2071	Medical Records and Health Information Technicians	0.673
29-2081	Opticians, Dispensing	0.686
29-2091	Orthotists and Prosthetists	0.678
29-2099	Health Technologists and Technicians, All Other	0.672
29-9011	Occupational Health and Safety Specialists	0.711
29-9012	Occupational Health and Safety Technicians	0.688
29-9091	Athletic Trainers	0.645
31-1011	Home Health Aides	0.645
31-1012	Nursing Aides, Orderlies, and Attendants	0.624
31-1013	Psychiatric Aides	0.662
31-2011	Occupational Therapist Assistants	0.649
31-2012	Occupational Therapist Aides	0.631
31-2021	Physical Therapist Assistants	0.649
31-2022	Physical Therapist Aides	0.632
31-9011	Massage Therapists	0.602
31-9091	Dental Assistants	0.645
31-9092	Medical Assistants	0.679
31-9093	Medical Equipment Preparers	0.660
31-9094	Medical Transcriptionists	0.703
31-9095	Pharmacy Aides	0.666
31-9096	Veterinary Assistants and Laboratory Animal Caretakers	0.634
33-1011	First-Line Supervisors/Managers of Correctional Officers	0.650
33-1012	First-Line Supervisors/Managers of Police and Detectives	0.669
33-1021	First-Line Supervisors/Managers of Fire Fighting and Prevention Workers	0.654
33-2011	Fire Fighters	0.626
33-2021	Fire Inspectors and Investigators	0.687
33-2022	Forest Fire Inspectors and Prevention Specialists	0.675
33-3011	Bailiffs	0.642
33-3012	Correctional Officers and Jailers	0.632
33-3021	Detectives and Criminal Investigators	0.674
33-3031	Fish and Game Wardens	0.651
33-3041	Parking Enforcement Workers	0.655

33-3051	Police and Sheriff's Patrol Officers	0.651
33-3052	Transit and Railroad Police	0.647
33-9011	Animal Control Workers	0.650
33-9021	Private Detectives and Investigators	0.689
33-9031	Gaming Surveillance Officers and Gaming Investigators	0.694
33-9032	Security Guards	0.647
33-9091	Crossing Guards	0.641
33-9092	Lifeguards, Ski Patrol, and Other Recreational Protective Service Workers	0.660
33-9099	Protective Service Workers, All Other	0.654
35-1011	Chefs and Head Cooks	0.660
35-1012	First-Line Supervisors/Managers of Food Preparation and Serving Workers	0.672
35-2011	Cooks, Fast Food	0.624
35-2012	Cooks, Institution and Cafeteria	0.643
35-2013	Cooks, Private Household	0.642
35-2014	Cooks, Restaurant	0.664
35-2015	Cooks, Short Order	0.648
35-2021	Food Preparation Workers	0.637
35-3011	Bartenders	0.649
35-3021	Combined Food Preparation and Serving Workers, Including Fast Food	0.642
35-3022	Counter Attendants, Cafeteria, Food Concession, and Coffee Shop	0.626
35-3031	Waiters and Waitresses	0.626
35-3041	Food Servers, Nonrestaurant	0.649
35-9011	Dining Room and Cafeteria Attendants and Bartender Helpers	0.595
35-9021	Dishwashers	0.605
35-9031	Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop	0.670
37-1011	First-Line Supervisors/Managers of Housekeeping and Janitorial Workers	0.649
37-1012	First-Line Supervisors/Managers of Landscaping, Lawn Service, and Groundskeeping Workers	0.650
37-2011	Janitors and Cleaners, Except Maids and Housekeeping Cleaners	0.611
37-2012	Maids and Housekeeping Cleaners	0.607
37-2021	Pest Control Workers	0.650
37-3011	Landscaping and Groundskeeping Workers	0.620
37-3012	Pesticide Handlers, Sprayers, and Applicators, Vegetation	0.648
37-3013	Tree Trimmers and Pruners	0.615
39-1011	Gaming Supervisors	0.706
39-1012	Slot Key Persons	0.654
39-1021	First-Line Supervisors/Managers of Personal Service Workers	0.657
39-2011	Animal Trainers	0.640
39-2021	Nonfarm Animal Caretakers	0.645
39-3011	Gaming Dealers	0.673
39-3012	Gaming and Sports Book Writers and Runners	0.690
39-3021	Motion Picture Projectionists	0.670
39-3031	Ushers, Lobby Attendants, and Ticket Takers	0.668

39-3091	Amusement and Recreation Attendants	0.665
39-3092	Costume Attendants	0.651
39-3093	Locker Room, Coatroom, and Dressing Room Attendants	0.649
39-4011	Embalmers	0.644
39-4021	Funeral Attendants	0.641
39-5011	Barbers	0.649
39-5012	Hairdressers, Hairstylists, and Cosmetologists	0.646
39-5091	Makeup Artists, Theatrical and Performance	0.657
39-5092	Manicurists and Pedicurists	0.676
39-5093	Shampooers	0.631
39-5094	Skin Care Specialists	0.663
39-6011	Baggage Porters and Bellhops	0.607
39-6012	Concierges	0.678
39-6021	Tour Guides and Escorts	0.670
39-6022	Travel Guides	0.696
39-6031	Flight Attendants	0.636
39-6032	Transportation Attendants, Except Flight Attendants and Baggage Porters	0.652
39-9011	Child Care Workers	0.656
39-9021	Personal and Home Care Aides	0.650
39-9031	Fitness Trainers and Aerobics Instructors	0.579
39-9032	Recreation Workers	0.654
39-9041	Residential Advisors	0.708
41-1011	First-Line Supervisors/Managers of Retail Sales Workers	0.662
41-1012	First-Line Supervisors/Managers of Non-Retail Sales Workers	0.708
41-2011	Cashiers	0.649
41-2012	Gaming Change Persons and Booth Cashiers	0.669
41-2021	Counter and Rental Clerks	0.659
41-2022	Parts Salespersons	0.668
41-2031	Retail Salespersons	0.666
41-3011	Advertising Sales Agents	0.712
41-3021	Insurance Sales Agents	0.719
41-3031	Securities, Commodities, and Financial Services Sales Agents	0.713
41-3041	Travel Agents	0.707
41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	0.706
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	0.694
41-9011	Demonstrators and Product Promoters	0.672
41-9012	Models	0.617
41-9021	Real Estate Brokers	0.708
41-9022	Real Estate Sales Agents	0.710
41-9031	Sales Engineers	0.714
41-9041	Telemarketers	0.688

41-9091	Door-To-Door Sales Workers, News and Street Vendors, and Related Workers	0.696
43-1011	First-Line Supervisors/Managers of Office and Administrative Support Workers	0.717
43-2011	Switchboard Operators, Including Answering Service	0.700
43-2021	Telephone Operators	0.695
43-3011	Bill and Account Collectors	0.714
43-3021	Billing and Posting Clerks and Machine Operators	0.724
43-3031	Bookkeeping, Accounting, and Auditing Clerks	0.723
43-3041	Gaming Cage Workers	0.683
43-3051	Payroll and Timekeeping Clerks	0.724
43-3061	Procurement Clerks	0.721
43-3071	Tellers	0.693
43-4011	Brokerage Clerks	0.715
43-4021	Correspondence Clerks	0.714
43-4031	Court, Municipal, and License Clerks	0.708
43-4041	Credit Authorizers, Checkers, and Clerks	0.721
43-4051	Customer Service Representatives	0.713
43-4061	Eligibility Interviewers, Government Programs	0.714
43-4071	File Clerks	0.685
43-4081	Hotel, Motel, and Resort Desk Clerks	0.706
43-4111	Interviewers, Except Eligibility and Loan	0.710
43-4121	Library Assistants, Clerical	0.678
43-4131	Loan Interviewers and Clerks	0.721
43-4141	New Accounts Clerks	0.717
43-4151	Order Clerks	0.701
43-4161	Human Resources Assistants, Except Payroll and Timekeeping	0.721
43-4171	Receptionists and Information Clerks	0.698
43-4181	Reservation and Transportation Ticket Agents and Travel Clerks	0.678
43-5011	Cargo and Freight Agents	0.707
43-5021	Couriers and Messengers	0.637
43-5031	Police, Fire, and Ambulance Dispatchers	0.702
43-5032	Dispatchers, Except Police, Fire, and Ambulance	0.719
43-5041	Meter Readers, Utilities	0.646
43-5051	Postal Service Clerks	0.649
43-5052	Postal Service Mail Carriers	0.638
43-5053	Postal Service Mail Sorters, Processors, and Processing Machine Operators	0.637
43-5061	Production, Planning, and Expediting Clerks	0.709
43-5071	Shipping, Receiving, and Traffic Clerks	0.645
43-5081	Stock Clerks and Order Fillers	0.640
43-5111	Weighers, Measurers, Checkers, and Samplers, Recordkeeping	0.675
43-6011	Executive Secretaries and Administrative Assistants	0.719
43-6012	Legal Secretaries	0.705

43-6013	Medical Secretaries	0.711
43-6014	Secretaries, Except Legal, Medical, and Executive	0.715
43-9011	Computer Operators	0.695
43-9021	Data Entry Keyers	0.694
43-9022	Word Processors and Typists	0.702
43-9031	Desktop Publishers	0.699
43-9041	Insurance Claims and Policy Processing Clerks	0.717
43-9051	Mail Clerks and Mail Machine Operators, Except Postal Service	0.648
43-9061	Office Clerks, General	0.699
43-9071	Office Machine Operators, Except Computer	0.662
43-9081	Proofreaders and Copy Markers	0.723
43-9111	Statistical Assistants	0.724
45-1011	First-Line Supervisors/Managers of Farming, Fishing, and Forestry Workers	0.659
45-1012	Farm Labor Contractors	0.658
45-2011	Agricultural Inspectors	0.684
45-2021	Animal Breeders	0.644
45-2041	Graders and Sorters, Agricultural Products	0.611
45-2091	Agricultural Equipment Operators	0.640
45-2092	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	0.620
45-2093	Farmworkers, Farm and Ranch Animals	0.637
45-3011	Fishers and Related Fishing Workers	0.621
45-3021	Hunters and Trappers	0.639
45-4011	Forest and Conservation Workers	0.637
45-4021	Fallers	0.610
45-4022	Logging Equipment Operators	0.651
45-4023	Log Graders and Scalers	0.670
47-1011	First-Line Supervisors/Managers of Construction Trades and Extraction Workers	0.671
47-2011	Boilermakers	0.638
47-2021	Brickmasons and Blockmasons	0.595
47-2022	Stonemasons	0.608
47-2031	Carpenters	0.622
47-2041	Carpet Installers	0.611
47-2042	Floor Layers, Except Carpet, Wood, and Hard Tiles	0.622
47-2043	Floor Sanders and Finishers	0.609
47-2044	Tile and Marble Setters	0.630
47-2051	Cement Masons and Concrete Finishers	0.624
47-2053	Terrazzo Workers and Finishers	0.608
47-2061	Construction Laborers	0.609
47-2071	Paving, Surfacing, and Tamping Equipment Operators	0.641
47-2072	Pile-Driver Operators	0.633
47-2073	Operating Engineers and Other Construction Equipment Operators	0.652
47-2081	Drywall and Ceiling Tile Installers	0.621

47-2082	Tapers	0.629
47-2111	Electricians	0.647
47-2121	Glaziers	0.626
47-2131	Insulation Workers, Floor, Ceiling, and Wall	0.610
47-2132	Insulation Workers, Mechanical	0.624
47-2141	Painters, Construction and Maintenance	0.607
47-2142	Paperhangers	0.610
47-2151	Pipelayers	0.637
47-2152	Plumbers, Pipefitters, and Steamfitters	0.637
47-2161	Plasterers and Stucco Masons	0.609
47-2171	Reinforcing Iron and Rebar Workers	0.606
47-2181	Roofers	0.607
47-2211	Sheet Metal Workers	0.624
47-2221	Structural Iron and Steel Workers	0.608
47-3011	Helpers--Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	0.613
47-3012	Helpers--Carpenters	0.619
47-3013	Helpers--Electricians	0.615
47-3014	Helpers--Painters, Paperhangers, Plasterers, and Stucco Masons	0.594
47-3015	Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters	0.611
47-3016	Helpers--Roofers	0.600
47-4011	Construction and Building Inspectors	0.685
47-4021	Elevator Installers and Repairers	0.646
47-4031	Fence Erectors	0.606
47-4041	Hazardous Materials Removal Workers	0.658
47-4051	Highway Maintenance Workers	0.613
47-4061	Rail-Track Laying and Maintenance Equipment Operators	0.624
47-4071	Septic Tank Servicers and Sewer Pipe Cleaners	0.636
47-4091	Segmental Pavers	0.638
47-5011	Derrick Operators, Oil and Gas	0.622
47-5012	Rotary Drill Operators, Oil and Gas	0.649
47-5013	Service Unit Operators, Oil, Gas, and Mining	0.643
47-5021	Earth Drillers, Except Oil and Gas	0.668
47-5031	Explosives Workers, Ordnance Handling Experts, and Blasters	0.652
47-5041	Continuous Mining Machine Operators	0.637
47-5042	Mine Cutting and Channeling Machine Operators	0.633
47-5051	Rock Splitters, Quarry	0.608
47-5061	Roof Bolters, Mining	0.612
47-5071	Roustabouts, Oil and Gas	0.627
47-5081	Helpers--Extraction Workers	0.629
49-1011	First-Line Supervisors/Managers of Mechanics, Installers, and Repairers	0.670
49-2011	Computer, Automated Teller, and Office Machine Repairers	0.671
49-2021	Radio Mechanics	0.669

49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers	0.645
49-2091	Avionics Technicians	0.673
49-2092	Electric Motor, Power Tool, and Related Repairers	0.651
49-2093	Electrical and Electronics Installers and Repairers, Transportation Equipment	0.653
49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment	0.657
49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay	0.666
49-2096	Electronic Equipment Installers and Repairers, Motor Vehicles	0.653
49-2097	Electronic Home Entertainment Equipment Installers and Repairers	0.659
49-2098	Security and Fire Alarm Systems Installers	0.648
49-3011	Aircraft Mechanics and Service Technicians	0.655
49-3021	Automotive Body and Related Repairers	0.636
49-3022	Automotive Glass Installers and Repairers	0.645
49-3023	Automotive Service Technicians and Mechanics	0.641
49-3031	Bus and Truck Mechanics and Diesel Engine Specialists	0.634
49-3041	Farm Equipment Mechanics	0.637
49-3042	Mobile Heavy Equipment Mechanics, Except Engines	0.636
49-3043	Rail Car Repairers	0.622
49-3051	Motorboat Mechanics	0.644
49-3052	Motorcycle Mechanics	0.641
49-3053	Outdoor Power Equipment and Other Small Engine Mechanics	0.645
49-3091	Bicycle Repairers	0.644
49-3092	Recreational Vehicle Service Technicians	0.641
49-3093	Tire Repairers and Changers	0.612
49-9011	Mechanical Door Repairers	0.623
49-9012	Control and Valve Installers and Repairers, Except Mechanical Door	0.644
49-9021	Heating, Air Conditioning, and Refrigeration Mechanics and Installers	0.634
49-9031	Home Appliance Repairers	0.644
49-9041	Industrial Machinery Mechanics	0.638
49-9042	Maintenance and Repair Workers, General	0.643
49-9043	Maintenance Workers, Machinery	0.646
49-9044	Millwrights	0.634
49-9045	Refractory Materials Repairers, Except Brickmasons	0.630
49-9051	Electrical Power-Line Installers and Repairers	0.634
49-9052	Telecommunications Line Installers and Repairers	0.640
49-9061	Camera and Photographic Equipment Repairers	0.689
49-9062	Medical Equipment Repairers	0.666
49-9063	Musical Instrument Repairers and Tuners	0.653
49-9064	Watch Repairers	0.683
49-9091	Coin, Vending, and Amusement Machine Servicers and Repairers	0.651
49-9092	Commercial Divers	0.638
49-9093	Fabric Menders, Except Garment	0.630
49-9094	Locksmiths and Safe Repairers	0.652

49-9095	Manufactured Building and Mobile Home Installers	0.626
49-9096	Riggers	0.633
49-9097	Signal and Track Switch Repairers	0.652
49-9098	Helpers--Installation, Maintenance, and Repair Workers	0.626
51-1011	First-Line Supervisors/Managers of Production and Operating Workers	0.673
51-2011	Aircraft Structure, Surfaces, Rigging, and Systems Assemblers	0.646
51-2021	Coil Winders, Tapers, and Finishers	0.646
51-2022	Electrical and Electronic Equipment Assemblers	0.656
51-2023	Electromechanical Equipment Assemblers	0.662
51-2031	Engine and Other Machine Assemblers	0.642
51-2041	Structural Metal Fabricators and Fitters	0.632
51-2091	Fiberglass Laminators and Fabricators	0.633
51-2092	Team Assemblers	0.646
51-2093	Timing Device Assemblers, Adjusters, and Calibrators	0.677
51-3011	Bakers	0.663
51-3021	Butchers and Meat Cutters	0.641
51-3022	Meat, Poultry, and Fish Cutters and Trimmers	0.638
51-3023	Slaughterers and Meat Packers	0.604
51-3091	Food and Tobacco Roasting, Baking, and Drying Machine Operators and Tenders	0.648
51-3092	Food Batchmakers	0.652
51-3093	Food Cooking Machine Operators and Tenders	0.667
51-4011	Computer-Controlled Machine Tool Operators, Metal and Plastic	0.652
51-4012	Numerical Tool and Process Control Programmers	0.675
51-4021	Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	0.634
51-4022	Forging Machine Setters, Operators, and Tenders, Metal and Plastic	0.650
51-4023	Rolling Machine Setters, Operators, and Tenders, Metal and Plastic	0.639
51-4031	Cutting, Punching, and Press Machine Setters, Operators, and Tenders, Metal and Plastic	0.641
51-4032	Drilling and Boring Machine Tool Setters, Operators, and Tenders, Metal and Plastic	0.647
51-4033	Grinding, Lapping, Polishing, and Buffing Machine Tool Setters, Operators, and Tenders, Metal and Plastic	0.648
51-4034	Lathe and Turning Machine Tool Setters, Operators, and Tenders, Metal and Plastic	0.640
51-4035	Milling and Planing Machine Setters, Operators, and Tenders, Metal and Plastic	0.642
51-4041	Machinists	0.652
51-4051	Metal-Refining Furnace Operators and Tenders	0.637
51-4052	Pourers and Casters, Metal	0.641
51-4061	Model Makers, Metal and Plastic	0.650
51-4062	Patternmakers, Metal and Plastic	0.654
51-4071	Foundry Mold and Coremakers	0.610
51-4072	Molding, Coremaking, and Casting Machine Setters, Operators, and Tenders, Metal and Plastic	0.630

51-4081	Multiple Machine Tool Setters, Operators, and Tenders, Metal and Plastic	0.646
51-4111	Tool and Die Makers	0.648
51-4121	Welders, Cutters, Solderers, and Brazers	0.645
51-4122	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders	0.643
51-4191	Heat Treating Equipment Setters, Operators, and Tenders, Metal and Plastic	0.641
51-4192	Lay-Out Workers, Metal and Plastic	0.656
51-4193	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	0.633
51-4194	Tool Grinders, Filers, and Sharpeners	0.656
51-5011	Bindery Workers	0.631
51-5012	Bookbinders	0.645
51-5021	Job Printers	0.649
51-5022	Prepress Technicians and Workers	0.698
51-5023	Printing Machine Operators	0.647
51-6011	Laundry and Dry-Cleaning Workers	0.639
51-6021	Pressers, Textile, Garment, and Related Materials	0.607
51-6031	Sewing Machine Operators	0.654
51-6041	Shoe and Leather Workers and Repairers	0.641
51-6042	Shoe Machine Operators and Tenders	0.639
51-6051	Sewers, Hand	0.667
51-6052	Tailors, Dressmakers, and Custom Sewers	0.665
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders	0.645
51-6062	Textile Cutting Machine Setters, Operators, and Tenders	0.637
51-6063	Textile Knitting and Weaving Machine Setters, Operators, and Tenders	0.628
51-6064	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	0.630
51-6091	Extruding and Forming Machine Setters, Operators, and Tenders, Synthetic and Glass Fibers	0.638
51-6092	Fabric and Apparel Patternmakers	0.680
51-6093	Upholsterers	0.630
51-7011	Cabinetmakers and Bench Carpenters	0.627
51-7021	Furniture Finishers	0.632
51-7031	Model Makers, Wood	0.650
51-7032	Patternmakers, Wood	0.642
51-7041	Sawing Machine Setters, Operators, and Tenders, Wood	0.641
51-7042	Woodworking Machine Setters, Operators, and Tenders, Except Sawing	0.645
51-8011	Nuclear Power Reactor Operators	0.708
51-8012	Power Distributors and Dispatchers	0.712
51-8013	Power Plant Operators	0.662
51-8021	Stationary Engineers and Boiler Operators	0.656
51-8031	Water and Liquid Waste Treatment Plant and System Operators	0.652
51-8091	Chemical Plant and System Operators	0.665
51-8092	Gas Plant Operators	0.669
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers	0.667

51-9011	Chemical Equipment Operators and Tenders	0.664
51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders	0.645
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	0.640
51-9022	Grinding and Polishing Workers, Hand	0.644
51-9023	Mixing and Blending Machine Setters, Operators, and Tenders	0.647
51-9031	Cutters and Trimmers, Hand	0.645
51-9032	Cutting and Slicing Machine Setters, Operators, and Tenders	0.646
51-9041	Extruding, Forming, Pressing, and Compacting Machine Setters, Operators, and Tenders	0.640
51-9051	Furnace, Kiln, Oven, Drier, and Kettle Operators and Tenders	0.637
51-9061	Inspectors, Testers, Sorters, Samplers, and Weighers	0.675
51-9071	Jewelers and Precious Stone and Metal Workers	0.685
51-9081	Dental Laboratory Technicians	0.690
51-9082	Medical Appliance Technicians	0.662
51-9083	Ophthalmic Laboratory Technicians	0.661
51-9111	Packaging and Filling Machine Operators and Tenders	0.644
51-9121	Coating, Painting, and Spraying Machine Setters, Operators, and Tenders	0.641
51-9122	Painters, Transportation Equipment	0.625
51-9123	Painting, Coating, and Decorating Workers	0.637
51-9131	Photographic Process Workers	0.681
51-9132	Photographic Processing Machine Operators	0.670
51-9141	Semiconductor Processors	0.655
51-9191	Cementing and Gluing Machine Operators and Tenders	0.626
51-9192	Cleaning, Washing, and Metal Pickling Equipment Operators and Tenders	0.622
51-9193	Cooling and Freezing Equipment Operators and Tenders	0.644
51-9194	Etchers and Engravers	0.656
51-9195	Molders, Shapers, and Casters, Except Metal and Plastic	0.635
51-9196	Paper Goods Machine Setters, Operators, and Tenders	0.649
51-9197	Tire Builders	0.612
51-9198	Helpers--Production Workers	0.626
53-1011	Aircraft Cargo Handling Supervisors	0.650
53-1021	First-Line Supervisors/Managers of Helpers, Laborers, and Material Movers, Hand	0.667
53-1031	First-Line Supervisors/Managers of Transportation and Material-Moving Machine and Vehicle Operators	0.682
53-2011	Airline Pilots, Copilots, and Flight Engineers	0.687
53-2012	Commercial Pilots	0.677
53-2021	Air Traffic Controllers	0.721
53-2022	Airfield Operations Specialists	0.707
53-3011	Ambulance Drivers and Attendants, Except Emergency Medical Technicians	0.646
53-3021	Bus Drivers, Transit and Intercity	0.662
53-3022	Bus Drivers, School	0.667
53-3031	Driver/Sales Workers	0.654

53-3032	Truck Drivers, Heavy and Tractor-Trailer	0.636
53-3033	Truck Drivers, Light or Delivery Services	0.636
53-3041	Taxi Drivers and Chauffeurs	0.668
53-4011	Locomotive Engineers	0.668
53-4012	Locomotive Firers	0.656
53-4013	Rail Yard Engineers, Dinkey Operators, and Hostlers	0.650
53-4021	Railroad Brake, Signal, and Switch Operators	0.634
53-4031	Railroad Conductors and Yardmasters	0.652
53-4041	Subway and Streetcar Operators	0.660
53-5011	Sailors and Marine Oilers	0.634
53-5021	Captains, Mates, and Pilots of Water Vessels	0.671
53-5022	Motorboat Operators	0.652
53-5031	Ship Engineers	0.653
53-6011	Bridge and Lock Tenders	0.656
53-6021	Parking Lot Attendants	0.649
53-6031	Service Station Attendants	0.629
53-6041	Traffic Technicians	0.704
53-6051	Transportation Inspectors	0.669
53-7011	Conveyor Operators and Tenders	0.657
53-7021	Crane and Tower Operators	0.648
53-7031	Dredge Operators	0.645
53-7032	Excavating and Loading Machine and Dragline Operators	0.640
53-7033	Loading Machine Operators, Underground Mining	0.634
53-7041	Hoist and Winch Operators	0.643
53-7051	Industrial Truck and Tractor Operators	0.631
53-7061	Cleaners of Vehicles and Equipment	0.616
53-7062	Laborers and Freight, Stock, and Material Movers, Hand	0.622
53-7063	Machine Feeders and Offbearers	0.634
53-7064	Packers and Packagers, Hand	0.597