Linking Advances in Artificial Intelligence to Skills, Occupations, and Industries

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Abstract: Prior episodes of automation have led to economic growth and also to many changes in the workplace. In some cases automation has substituted for labor and in other cases automation has complemented labor. We expect that artificial intelligence (AI) will boost economic growth while affecting labor in different ways. The link between AI and labor is complex, however. Our paper provides a method that we believe can help researchers and policy makers to better understand the link between AI and labor. We also demonstrate the method in several applications, including predicting which occupation descriptions will change the most due to advances in AI.

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1. Introduction

Economists now widely believe that innovation drives economic growth (Romer 1990; Solow 1957). Artificial Intelligence (AI) has great promise as an innovation that may lead to economic growth (CEA 2016). For example, according to Graetz and Michaels (2015), robotics, an advanced technology with similarities to AI, added an estimated 0.37 percentage points of annual GDP growth between 1993 and 2007, on average, for the 17 countries in their sample (accounting for about one-tenth of GDP growth during this time period). The authors note that these effects are of similar magnitude to the impact of steam engines on growth in the UK.

However, while AI may boost growth, the effect on labor is less clear. Historically there is empirical evidence that automation can both complement and substitute for labor. Autor and Salomons (2017) find that, even as employment falls within an industry as industry-specific productivity increases, the negative own-industry employment effect is more than offset by positive spillovers to other sectors. Similarly, in a study examining the effects of ecommerce on brick-and-mortar retail stores, Mandel (2017) found that new jobs created at fulfillment and call centers more than made up for any job losses at department stores caused by the rise of ecommerce. In the specific case of robots, research provides mixed findings, with some researchers finding no effect of robots on labor (Graetz and Michaels 2015), and others finding evidence that robot adoption leads to job losses (Acemoglu and Restrepo 2017). To date, however, there has been little systematic empirical research on the link between AI and labor.

Our paper provides a method that we believe can help researchers and policy makers to better understand the link between AI and labor. At a conceptual level, we first point out that "AI" is a broad term used to describe a number of different types of technologies, each of which might affect labor in different ways, and each of which might advance at its own rate. In addition, "labor" can be described via the bundle of skills that are used for any specific occupation (Autor and Handel 2013; Macrory, Westerman, Brynjolfsson 2015). This task-based approach allows us to examine the specific skills that comprise each occupation, and allow for an in-depth analysis of the specific components of a job. In other words, these skills can be aggregated into occupations, and from occupations can be aggregated into different industries. Our method—which is described in detail below—essentially links the different categories of AI to different types of skills. This then allows us to model how advances in AI affect different skills, occupations, and industries. We then explore these effects using three different simulations, and finally conclude with a discussion of policy implications and other next steps.

2. Related Literature

There has been little systematic work on the effect of artificial intelligence on the economy. Notable exceptions are studies by Frey and Osborne (2013), the Organization for Economic Co-operation and Development (OECD), Mann and Puttman (2017), and the McKinsey Global Institute (MGI).

Frey and Osborne (2013) attempt to determine how susceptible jobs may be to automation to provide an idea of the impact automation could have on the US labor force. The authors focus particularly on machine learning and its application to mobile robotics, and propose a model to predict the extent of computerization's impact on non-routine tasks. They note potential engineering bottlenecks at tasks involving high levels of perception or manipulation, creative intelligence, and social intelligence. After categorizing tasks by their susceptibility to automation, Frey and Osborne map these tasks to the O*NET job survey which provides open-ended descriptions of skills and responsibilities involved in an occupation over time. Integrating this dataset with employment and wage data from the Bureau of Labor Statistics (BLS) allows the authors to propose certain subsets of the labor market that may be at high, medium, or low risk of automation. The study finds that 47% of US employment is at high risk to computerization. It should be noted that this study is at an aggregate level and does not examine how firms may react, any labor saving innovations that could arise, or potential productivity or economic growth.

Frey and Osborne's work has also been applied by researchers in other countries – mapping Frey and Osborne's occupation-level findings to German labor market data, Brzeski and Burk (2015) suggest that 59% of German jobs may be highly susceptible to automation, while conducting that same analysis in Finland, Pajarinen and Rouvinen (2014) suggest that 35.7% of Finnish jobs are at high risk to automation.

The OECD Report similarly set out to estimate the automatability of jobs across 21 OECD countries. The OECD argues that it will be certain tasks that will be displaced and that the extent that bundles of tasks differ within occupations and across countries may make certain occupations less prone to automation than Frey and Osborne predicted. Relying upon the task categorization done by Frey and Osborne, the authors map task susceptibility to automation to

US data from the Programme for the International Assessment of Adult Competencies (PIAAC), a micro-level data source containing indicators on socio-economic characteristics, skills, job-related information, job-tasks, and competencies at the individual level. They then construct a model using the PIAAC to create a predicted susceptibility to automation based off of the observables in the PIAAC data to mirror the automatability score that Frey and Osborne created. This model is then applied at the worker-level across all the PIAAC data to predict how susceptible occupations may be to automation. By conducting the analysis at the individual level, the OECD argues that it is better able to account for task variation between individuals within the same occupation. As a result, the report suggests that Frey and Osborne overestimated the extent to which occupations would be susceptible to automation. The OECD Report argues that only 9% of jobs in the US and across OECD countries will be highly susceptible to automation. The report further suggests that the percent can vary across OECD countries, ranging from 6% (in Korea) up to 12% (in Austria).

While both the Frey and Osborne work and the OECD Report examine the effect of technology advances on occupations, they take a different approach than we do in this study. Both reports aim to predict the extent to which jobs will be substituted for technology, while we remain agnostic to whether the advances in technology will serve as substitutes or complements. Further, both studies take a broader view of automation, examining the impact of artificial intelligence as well as robotics. For our simulation, we focus only on advances in artificial intelligence as defined by the metrics from the AI research literature as collected by the Electronic Frontier Foundation (EFF). While we will be conducting the analysis at the occupation-level, similar to Frey and Osborne, another key difference is that we will be relying on quantitative, archival inputs from the AI research literature to measure progress in AI technologies and identify affected tasks and skills. In contrast, Frey and Osborne examined task susceptibility by surveying experts in the field.

Mann and Puttman (2017) take a different approach to analyze the effects of automation on employment. In their study, the authors rely on information provided from granted patents. They apply a machine learning algorithm to all US patents granted from 1976 to 2014 to identify patents related to automation (an automation patent is defined as a "device that operates independently from human intervention and fulfills a task with reasonable completion"). They then link the automation patents to the industries they are likely to be used in, and identify which areas in the US that these industries are related in. By examining economic indicators in comparison to the density of automation patents used in an area, Mann and Puttman find that though automation causes manufacturing employment to fall, it increases employment in the service sector, and overall has a positive impact on employment.

In work focused solely on AI, in June 2017, the McKinsey Global Institute published an independent discussion paper examining trends in investment in artificial intelligence, the prevalence of AI adoption, and how AI is deployed by companies that have started to use the technology (MGI Report 2017). The authors adopted a fairly narrow definition of AI, focusing only on AI technology which is programmed to conduct one set task. The MGI report conducted their investigation with a multi-method approach: it surveyed executives at over 3,000 international firms, interviewed industry experts, and analyzed investment flows using third party venture capital, private equity, and mergers & acquisitions data. Using the data collected, the MGI report attempts to answer questions regarding adoption by sector, size, and geography, to look at performance implications of adoption, and to examine potential impacts to the labor market.

Work regarding automation and artificial intelligence are increasingly important to both the private sector and to policy-makers. In addition to the reports discussed above by the OECD and MGI, other large organizations have begun documenting advances in and conducting analysis around artificial intelligence as well. Deloitte authored an Artificial Intelligence Innovation Report, containing a variety of case studies examining the increased use of artificial intelligence in consumer goods. Further, the Council of Economic Advisors in the United States included a chapter on Technology and Innovation in its 2016 Economic Report of the President (2016 ERP), and the Association of Southeast Asian Nations commissioned a survey and conducted qualitative data gathering to investigate which industries and countries may be more or less affected by advances in technology (ASEAN Report). Without proper knowledge of what to expect as artificial intelligence becomes more prevalent, businesses and governments will be unable to know the proper way to react and make decisions.

3. Methods

In constructing the simulation to measure the impact of artificial intelligence on occupations and industries in the United States, we rely upon 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 experiment is a pilot project that aims to track progress across a variety separate artificial intelligence categories, such as abstract strategy games and image recognition for example. For each of the categories, the EFF monitors progress in the field drawing on data from a variety of sources, including blog posts and websites focused on subfields of machine learning, academic literature, and review articles. The EFF aims to create the first integrated database that provides the state of the art across a variety of artificial intelligence categories in one single place, and therefore provides researchers, policy makers, and technology users with a thorough understanding of the state and the rate of development of the field.

The O*NET database is a comprehensive online database that provides occupational definitions for professions in the modern day American workplace. Since the 1990s, the US Department of Labor has developed and maintained the database to provide up-to-date information as the nature of the occupations listed changes. For each occupation, O*NET provides information regarding personal requirements, personal characteristics, experience requirements, job requirements, and the state of the labor market. For the purposes of our study, we focus on job requirements. O*NET maintains a list of 52 distinct skills, and in each occupation's job requirements, it notes how important and prevalent each skill is in the relevant occupation.

For our simulation, we rely upon the EFF AI Progress Measurement dataset to track the rate of change across the sixteen separate categories of metrics the EFF tracks. For each of the categories, we first integrate all the different metrics tracked to get a comprehensive understanding of the pace of progress in the AI subfield corresponding to the category of metrics. This can be an intricate process, as measures within a category can utilize different scales and present distinct results. To provide an illustrative example, Figure 1 shows the data for the various metrics of image recognition tracked by the EFF.

For the image recognition category, the EFF provides eight separate metrics. To calculate the slope measuring the progress in image recognition as a whole, each metric must first be scaled appropriately. Next, progress is calculated on a per-metric basis using a logarithmic function based on the error rate. Finally, scores are aggregated across the metrics provided to reach a category-level score. For some AI categories, at the time of publication, the EFF either provided very little or no information regarding past progress. For those categories, the slope measuring progress was set equal to zero. Table 1 shows the slopes used for each of the EFF AI categories.

Next, we map the EFF AI categories to the list of 52 skills that the O*NET database uses to describe job requirements. To do so, we construct a matrix that connects the two. In the future, we plan to survey a variety of academic experts in the fields of artificial intelligence and computer science to get estimates of how each of the AI categories corresponds to O*NET skills, and use these estimates to develop a more fine-tuned matrix. For now, we rely instead on a matrix constructed using inputs from a number of computer science PhD students along with our best estimate of how the AI categories map to the O*NET skills. As such, this initial matrix is rudimentary and less nuanced than we hope our final matrix will be, however, it provides us with a tool to conduct a preliminary investigation.

With the matrix, we are able to connect the EFF categories to the O*NET skills, and can then measure the relative effect of advances in AI technology on the different skills listed by O*NET. We can then use the O*NET occupational definitions to evaluate the impact of AI technology advances on each occupation by weighting the effect of AI technology on each skill by the skill's prevalence and importance for each job. We aggregate the impact across all skills at the occupation-level to create an effect score for each job. While the value of the score itself is arbitrary, it allows us to compare the relative impact of AI technology across a variety of occupations.

Finally, from the occupation level, we have used the Bureau of Labor Statistics' Occupational Employment Statistics data to estimate the impact of artificial intelligence on an industry level. We do this by weighting each occupation-level impact score by the prevalence of an occupation in an industry and aggregating across all occupations within an industry. As with the occupation-level scores, the measure itself is arbitrary, but it allows for a comparison of the relative effect of AI technology across industries.

This methodology is not precise – its accuracy relies on properly combining a variety of different measures from the EFF Progress Measurement experiment and upon the validity of the O*NET job definitions. It also assumes that the matrix used to map the AI metrics with the O*NET skills properly weights each AI metric such that we are able to accurately measure how each skill is impacted by an advance in the relevant AI subfield. Further, this simulation does not allow us to speak to whether AI is serving as a substitute or complement to the occupations it effects – rather, it only suggests which occupations have skills that may be affected by advances in AI technology. Despite these shortcomings, we believe that this methodology provides a path to begin a preliminary investigation into the distributional impact of AI across occupations and industries.

4. Results

Historical Progress in AI

Using the progress slopes as calculated above, we were able to identify a list of occupations that presumably were the most impacted by AI technology over the last few years. To check the validity of our methodology, we examined the correlation between the occupation-level impact score and whether the BLS was planning on changing the official occupational definition for each job in 2018. The last updates to BLS occupation definitions was in 2010, so presumably, the occupations most impacted by AI from 2010 through 2016, when the decisions were made regarding which occupations to update, would be more likely to have changed in nature and require an update of their BLS definition.

Table 2 lists the top ten most and least affected occupations based on the methodology described above. For three of the most affected occupations, the BLS definition will be updated in 2018, while none of the least affected occupations will be receiving an updated definition. Figure 2 graphically charts the distribution of the occupational impact scores. Columns in red represent occupations that will be receiving updated definitions in 2018, while occupations in blue will not be updating their BLS definitions.

We conducted an analysis to identify whether there was any statistically significant correlation between the occupation-level impact score and whether an occupation was scheduled to receive a definition change. We found a statistically significant correlation coefficient of 0.0735 ($p=0.0412$) between the impact score and a scheduled definition change. Because the impact score is arbitrary, it is difficult to interpret the magnitude of this coefficient, however, as we hoped, it confirms a positive and significant relationship between the impact scores and definition changes.

As a follow up to this, we also conducted an analysis to investigate whether there was any correlation between the occupation impact scores and changes in employment or wages from 2010 to 2016. While there was no significant correlation between effect scores and employment, there was a statistically significant correlation coefficient of -0.1682 (p=0.000) between impact scores and annual wages. While we caution reading too much into these initial results, this could suggest that while AI does not have a large directional impact on employment figures, it may depress wages in affected occupations.

Forward Looking Simulations

After examining the correlation between historical progress and labor statistics and changes in the O*NET definitions, we next turned to conducting forward-looking simulations. For each simulation, we have analyzed the potential impact on occupations and industries based on a hypothetical advancement in one AI category holding all others constant. We have conducted the simulation for the following three categories: image recognition, speech recognition, and real time video games. As stated above, the occupation- and industry-level scores provided by our simulation are arbitrary, but by comparing values we can get a sense of the relative impact and the distribution of the effect of advances in various AI technologies on occupations and industries.

Figures 3-5 show the distribution of effect scores across occupations for each category. The shape of the distribution reflects how evenly the impact of an advancement in each category would impact occupations listed in the O*NET database. While the distributions look relatively similar, the line of best fit for each chart shows that the effect of real time video games is less even across occupations than for the other two AI categories. Similarly, Figures 6-8 show the distribution of effect scores across industries for each AI category.

Again using the slope of the line of a best fit as a measure of uniformness of effect, we see that, similarly to the effect across occupations, an advancement in real time video game technology would have more variance in effect across industries compared to an advancement in image or speech recognition technology.

In addition to the charts showing the shape of the effect distributions, these simulations can provide estimates of which occupations and industries will be the most and least impacted by the advancements in each of the selected AI categories. Table 3 shows the ten most impacted industries and occupations, while Table 4 shows the ten least effected industries and occupations.

Across all three manipulations, it appears that the transportation industry and occupations associated with transportation industries will be among the most affected by an advancement in AI technology. Aside from that commonality, we see that the most impacted occupations and industries change quite dramatically depending on which AI category we manipulate.

The least affected occupations and industries appear to be those associated with service industries. We see that across manipulations, restaurant services and food services-related industries and occupations appear to be among the least impacted regardless of which AI category is manipulated. Other service industry occupations also appear frequently on the lists of least impacted occupations, including housekeeping and hospitality-related occupations.

5. Implications for Future Work

The big question that has grabbed policymakers and pundits is: will artificial intelligence take all the jobs? Our take is that the answer is “no”. In prior episodes, automation has led to some job displacement, but also to the creation of many new jobs. In fact, automation appear to complement more jobs than it substitutes. We expect that it will be the same with AI. In order to understand the effects of AI on labor, however, more work needs to be done linking advances in AI to occupations and skills.

In this paper, we develop such a methodology, and apply it in a couple of specific cases, including a correlation between advances in AI to actual changes to occupational descriptions, and a prediction about which occupations and industries will be most affected by further advances in AI. Our methodology should be useful to other researchers and policy makers studying the effect of advances in AI on skills, occupations and industry. For example, future studies could make use of our methodology to study how a rapid increase in certain types of AI may have distributional effects that vary by occupations, industry or geography. Our methodology would benefit from more research to create a more systematic link between AI categories and skills.

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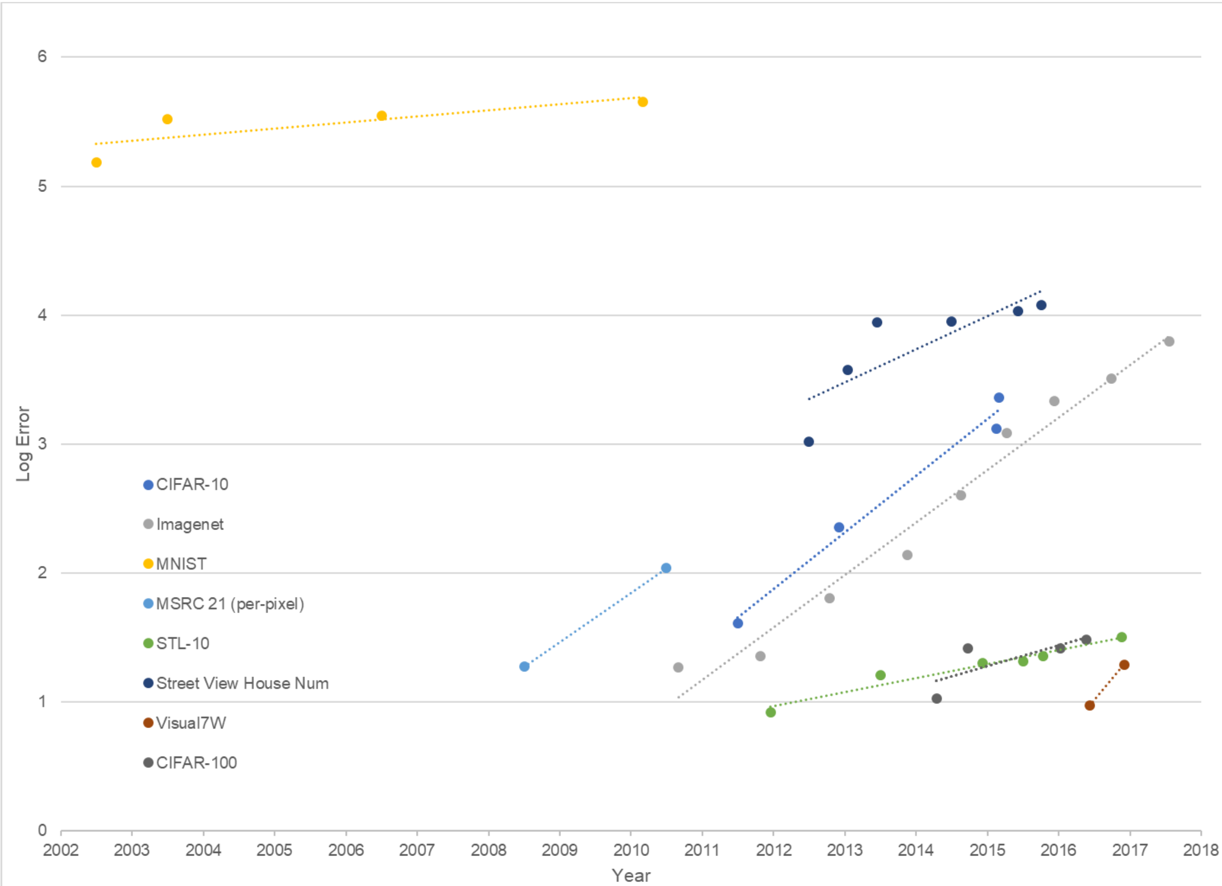

FIGURE 1. PROGRESS ACROSS EFF IMAGE RECOGNITION MEASURES

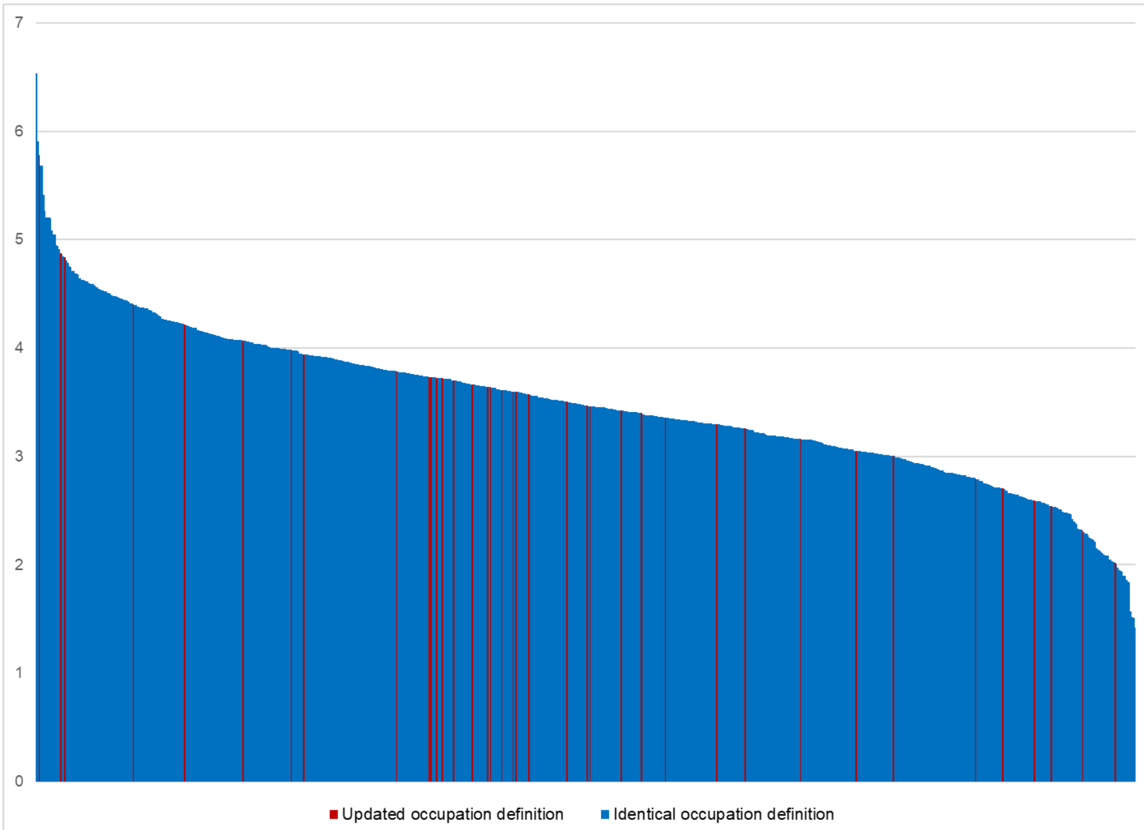

FIGURE 2. DISTRIBUTION OF OCCUPATION EMPLOYMENT EFFECT SCORES BASED ON HISTORICAL PROGRESS OF EFF METRICS

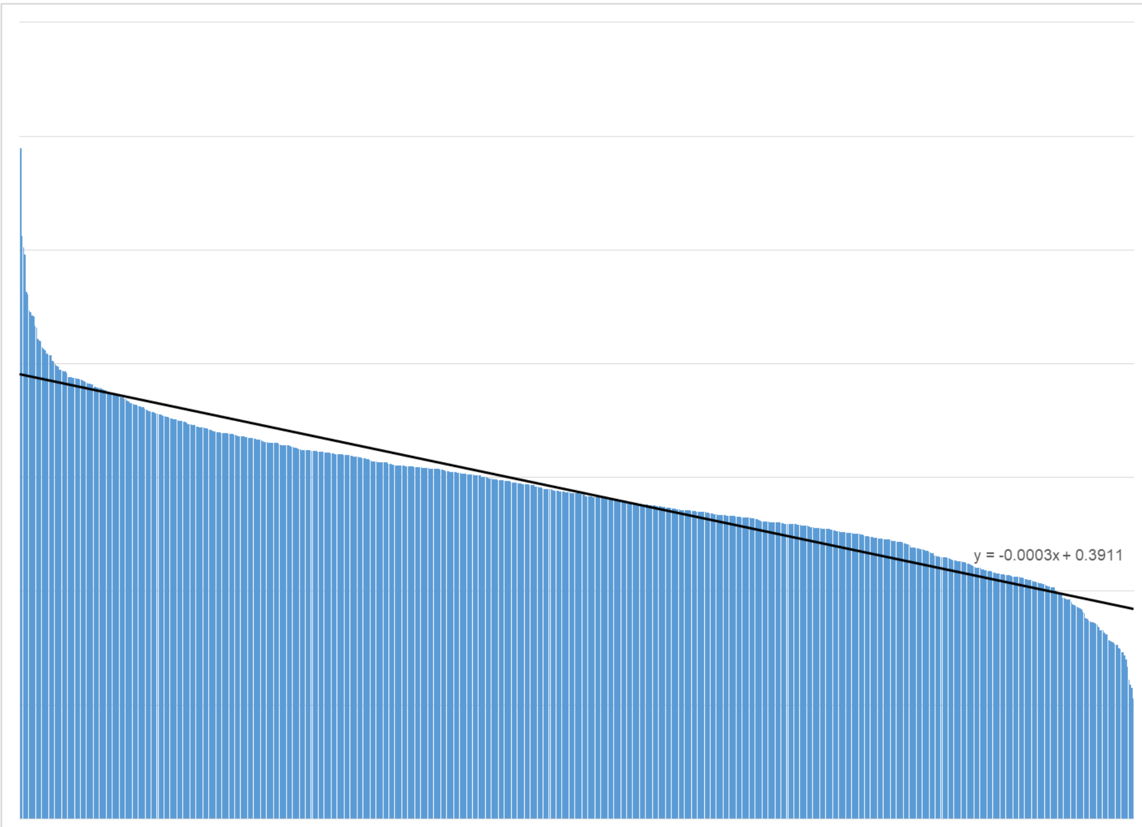

FIGURE 3. DISTRIBUTION OF OCCUPATION EFFECT SCORES – IMAGE RECOGNITION

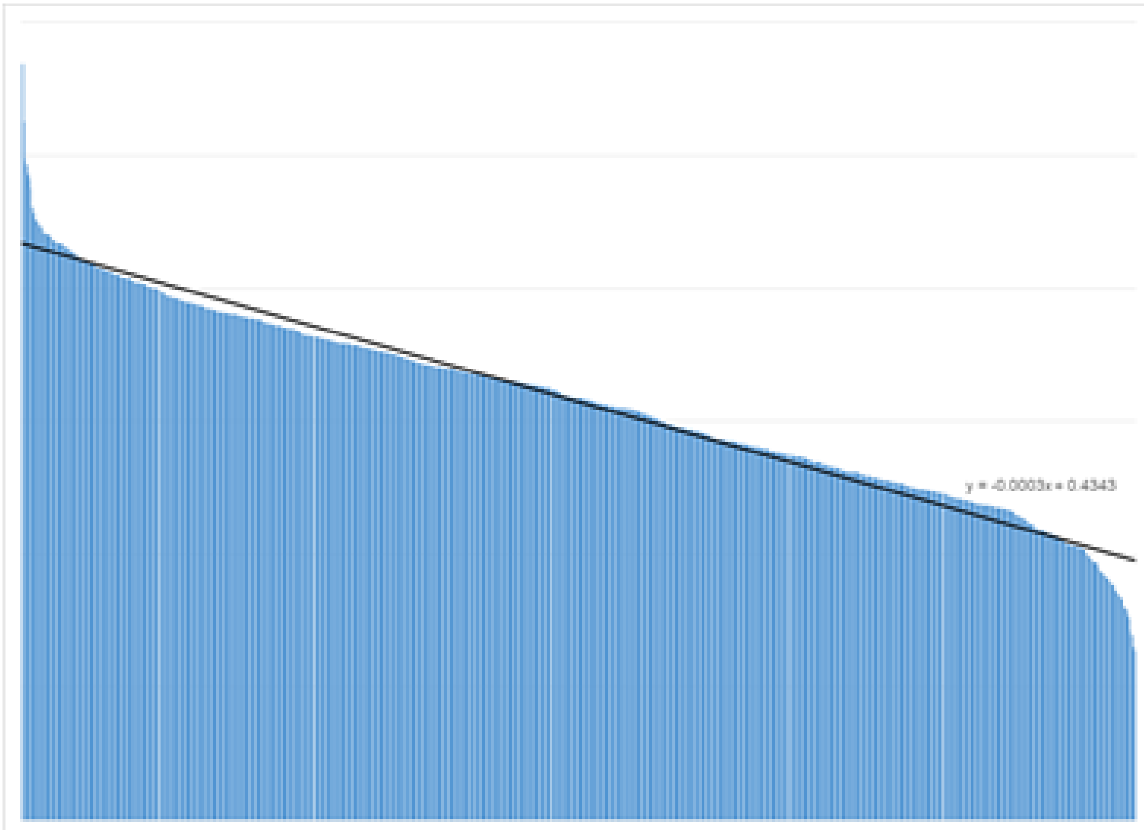

FIGURE 4. DISTRIBUTION OF OCCUPATION EFFECT SCORES – SPEECH RECOGNITION

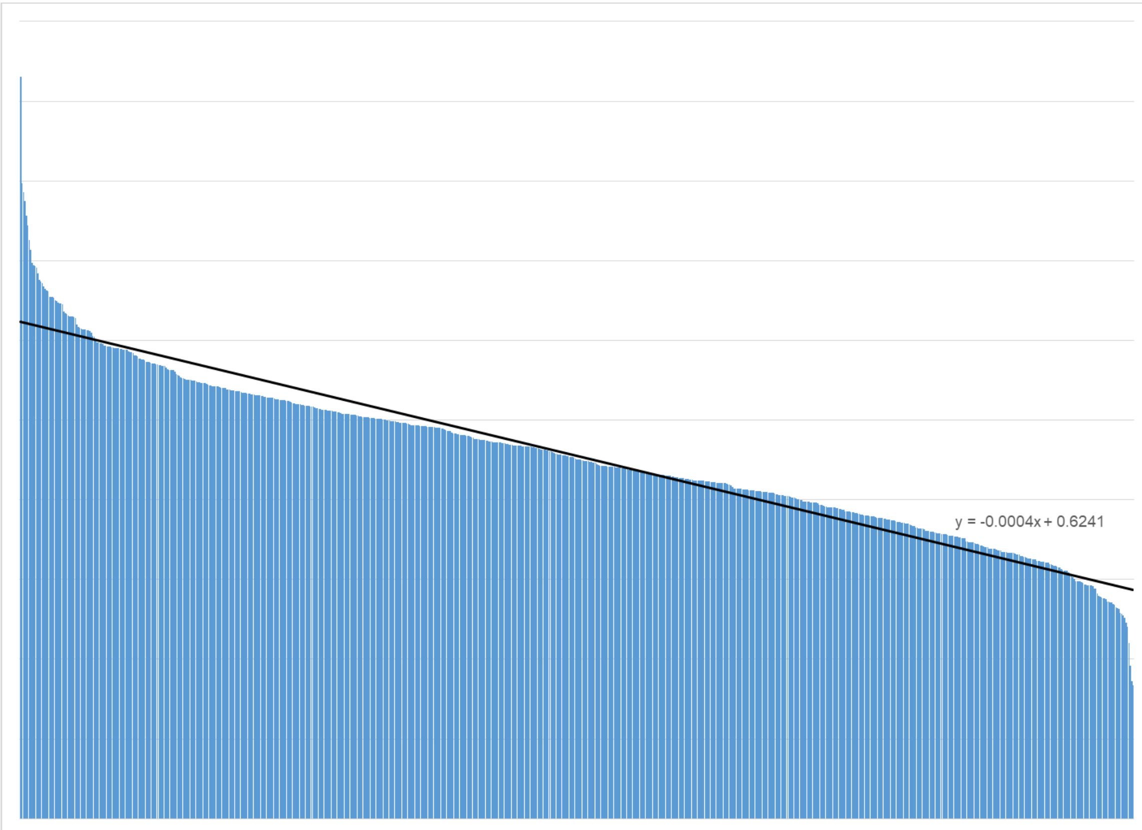

FIGURE 5. DISTRIBUTION OF OCCUPATION EFFECT SCORES – REAL TIME VIDEO GAMES

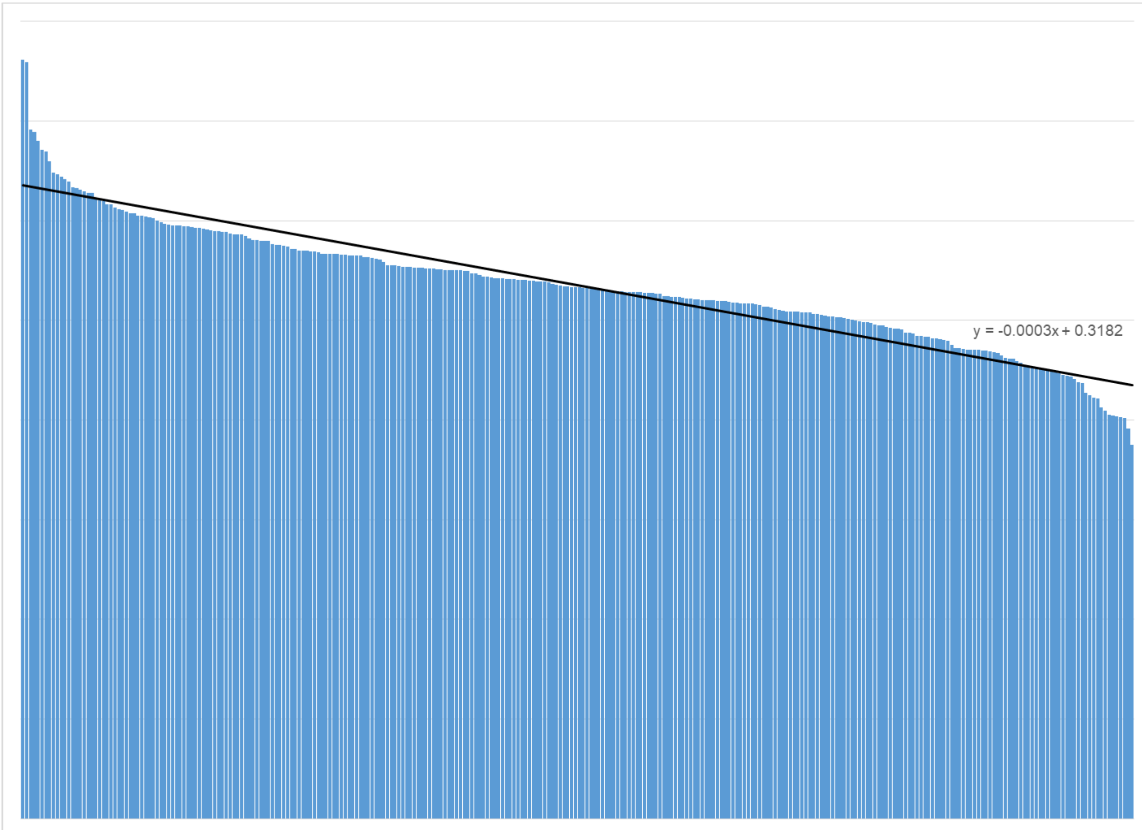

FIGURE 6. DISTRIBUTION OF INDUSTRY EFFECT SCORES – IMAGE RECOGNITION

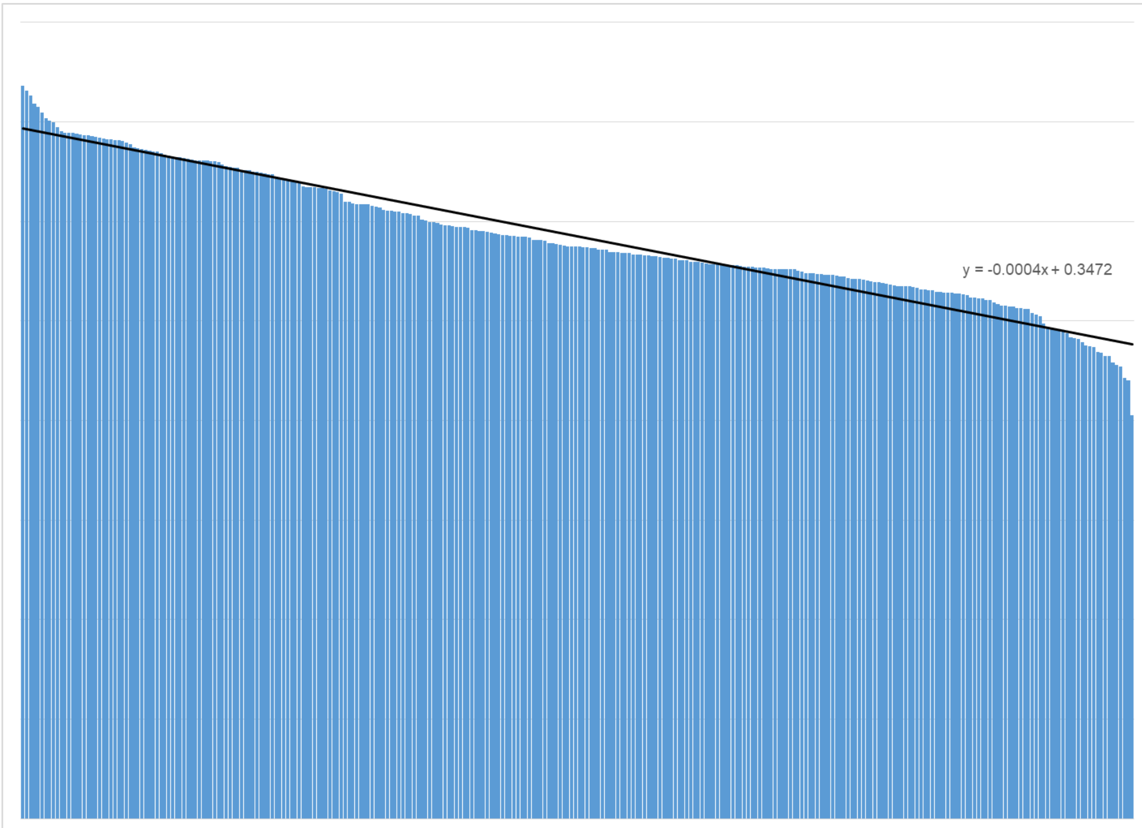

FIGURE 7. DISTRIBUTION OF INDUSTRY EFFECT SCORES – SPEECH RECOGNITION

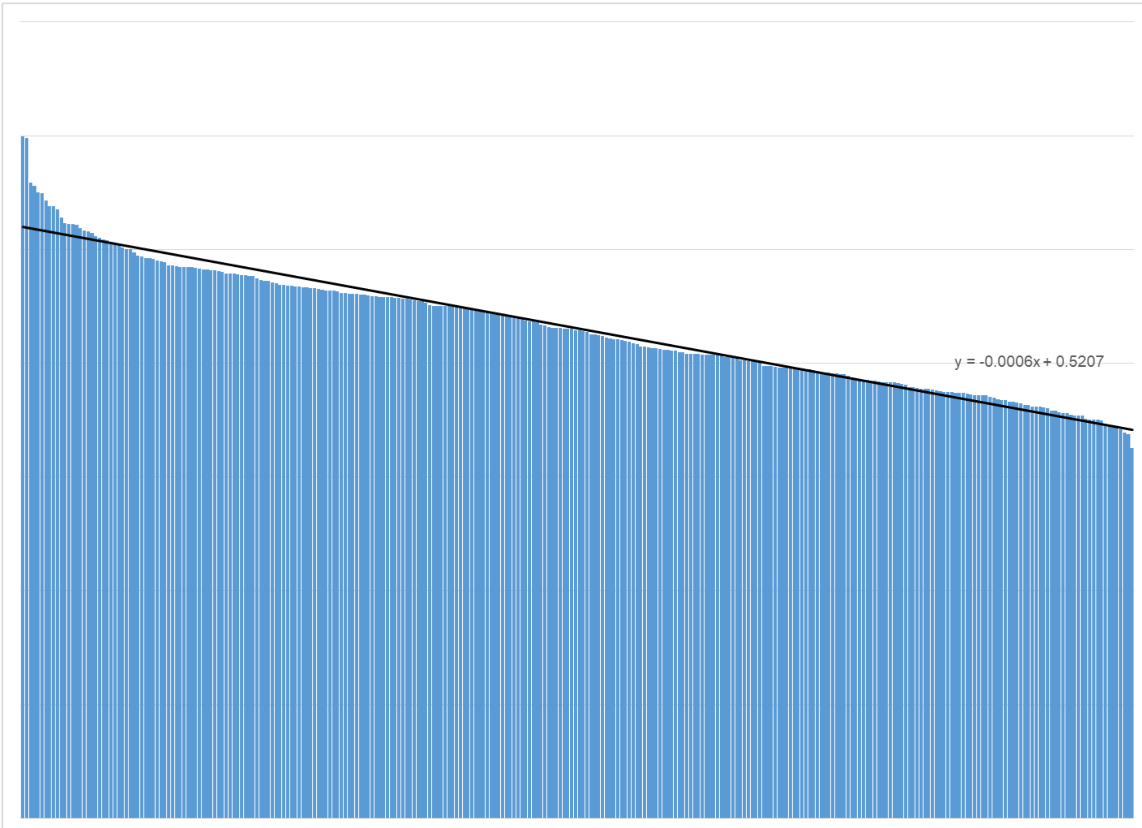

FIGURE 8. DISTRIBUTION OF INDUSTRY EFFECT SCORES – REAL TIME VIDEO GAMES

TABLE 1 — SLOPE OF PROGRESS IN EFF AI CATEGORIES

Metric	Slope
Abstract Strategy Games	0.0180
Real-Time Video Games	0.2710
Image Recognition	0.2300
Visual Question Answering	0.1490
Video Recognition	0.0000
Generating Images	0.0925
Reading Comprehension	0.1890
Language Modeling	0.0127
Conversation	0.0000
Translation	0.0091
Speech Recognition	0.0810
Solving Constrained, Well-Specified Technical Problems	0.0000
Solving Real-World Technical Problems	0.0000
Generating Computer Programs from Specifications	0.0000
Automated Hacking Systems	0.0000
Pedestrian Detection for Self-Driving Vehicles	0.0000

Notes: Progress measured using logarithmic functions incorporating the various measures provided by the EFF.

Source: EFF.

TABLE 2— MOST AND LEAST IMPACTED OCCUPATIONS BY EFF HISTORICAL AI PROGRESS

	Most Impacted		**Least Impacted**	
	Occupations	Scheduled Definition	Occupations	Scheduled Definition
1	Airline Pilots, Copilots, and Flight Engineers	✓	Models	
2	Physicists		Telemarketers	
3	Surgeons	✓	Locker Room, Coatroom, and Dressing Room	
4	Commercial Pilots	✓	Graders and Sorters, Agricultural Products	
5	Air Traffic Controllers		Shampooers	
6	Dentists, General		Maids and Housekeeping Cleaners	
7	Biochemists and Biophysicists		Cleaners of Vehicles and Equipment	
8	Oral and Maxillofacial Surgeons		Slaughterers and Meat Packers	
9	First-Line Supervisors of Fire Fighting and Prevention Workers		Dining Room and Cafeteria Attendants and Bartender Helpers	
10	Microbiologists		Food Servers, Nonrestaurant	

Notes: Impact measured by constructed employment effect scores. Occupations as listed by the O*NET database.

Source: EFF; O*NET; BLS.

TABLE 3 — MOST IMPACTED OCCUPATIONS AND INDUSTRIES BY EFF AI CATEGORY

	Image Recognition		**Speech Recognition**		**Real Time Video Games**	
	Occupations	Industries	Occupations	Industries	Occupations	Industries
1	Airline Pilots, Copilots, and	Inland Water Transportation	Physicists	Scientific Research and Development	Airline Pilots, Copilots, and Flight	Nonscheduled Air Transportation
2	Commercial Pilots	Nonscheduled Air Transportation	Air Traffic Controllers	Nonscheduled Air Transportation	Surgeons	Inland Water Transportation
3	Physicists	Other Pipeline Transportation	Psychologists, All Other	Architectural, Engineering, and Related	Commercial Pilots	Other Pipeline Transportation
4	Air Traffic Controllers	Deep Sea, Coastal, and Great Lakes	Biochemists and Biophysicists	Other Ambulatory Health Care	Dentists, General	Metal Ore Mining
5	Captains, Mates, and Pilots of	Pipeline Transportation of Crude Oil	Airline Pilots, Copilots, and Flight	Federal Executive Branch (OES	Firefighters	Other Ambulatory Health Care
6	Architects, Except Landscape	Architectural, Engineering, and Related	Surgeons	Securities and Commodity Exchanges	Oral and Maxillofacial Surgeons	Coal Mining
7	Surgeons	Other Ambulatory Health Care	Speech-Language Pathologists	Other Pipeline Transportation	Manufactured Building and Mobile Home	Rail Transportation
8	Forensic Science Technicians	Rail Transportation	Biological Scientists, All Other	Outpatient Care Centers	First-Line Supervisors of Fire Fighting	Pipeline Transportation of Crude Oil
9	First-Line Supervisors of Fire	Metal Ore Mining	Anesthesiologi sts	Monetary Authorities-Central Bank	Air Traffic Controllers	Logging
10	Biochemists and Biophysicists	Scenic and Sightseeing Transportation,	Microbiologist s	Pipeline Transportation of Crude Oil	Captains, Mates, and Pilots of Water	Deep Sea, Coastal, and Great Lakes

Notes: Impact measured by constructed employment effect scores. Industry level determined by 4-digit NAICS code. Occupations as listed by the O*NET database.

Source: EFF; O*NET; BLS OES.

TABLE 4 — LEAST IMPACTED OCCUPATIONS AND INDUSTRIES BY EFF AI CATEGORY

	Image Recognition		Speech Recognition		Real Time Video Games	
	Occupations	Industries	Occupations	Industries	Occupations	Industries
1	Telemarketers	Restaurants and Other Eating Places	Pressers, Textile, Garment, and	Services to Buildings and Dwellings	Telemarketers	Business Support Services
2	Locker Room, Coatroom,	Special Food Services	Cleaners of Vehicles and Equipment	Drycleaning and Laundry Services	Models	Restaurants and Other Eating Places
3	Models	Services to Buildings and Dwellings	Models	Support Activities for Crop	Locker Room, Coatroom, and Dressing Room	Rooming and Boarding Houses
4	Graders and Sorters, Agricultural	Rooming and Boarding Houses	Graders and Sorters, Agricultural	Animal Slaughtering and Processing	Door-to-Door Sales Workers, News and	Traveler Accommodation
5	Slaughterers and Meat Packers	Amusement Parks and Arcades	Slaughterers and Meat Packers	Restaurants and Other Eating Places	Graders and Sorters, Agricultural	Amusement Parks and Arcades
6	Shampooers	Drycleaning and Laundry Services	Dishwashers	Apparel Accessories and Other	Proofreaders and Copy Markers	Grocery Stores
7	Cooks, Fast Food	Grocery Stores	Mine Shuttle Car Operators	Special Food Services	Tour Guides and Escorts	Special Food Services
8	Maids and Housekeeping Cleaners	Traveler Accommodation	Maids and Housekeeping Cleaners	Rooming and Boarding Houses	Telephone Operators	Department Stores
9	Dining Room and Cafeteria Attendants	Gasoline Stations	Dining Room and Cafeteria Attendants and	Other Leather and Allied Product	Court, Municipal, and License Clerks	Agencies, Brokerages, and Other
10	Pressers, Textile, Garment, and	Specialty Food Stores	Packers and Packagers, Hand	Cut and Sew Apparel Manufacturing	Funeral Attendants	Beer, Wine, and Liquor Stores

Notes: Impact measured by constructed employment effect scores. Industry level determined by 4-digit NAICS code. Occupations as listed by the O*NET database.

Source: EFF; O*NET; BLS OES.