Online Appendix for

Occupational, Industry, and Geographic Exposure to Artificial Intelligence: A Novel Dataset and Its Potential Uses

Appendix A: Construction of the Application-Ability Relatedness Matrix

We link AI applications with the set of abilities in the O*NET database using approximately 2,000 survey responses from "gig workers" from Amazon's Mechanical Turk (mTurk) web service. mTurk functions as a crowdsourced internet marketplace that facilitates 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).[1] We rely on these mTurk survey responses to construct a matrix connecting the AI applications to the O*NET occupation-level ability data.

To link the AI applications to workplace abilities, for each of the 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 approximately 2,000 mTurkers residing in the United States (we solicited answers from approximately 200 respondents for each of the ten AI applications). 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 the 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

[1] We also test the sensitivity of the survey responses to using samples based on education-level or subject matter expertise as well as a focus group of computer scientists in Section 3.3.1.

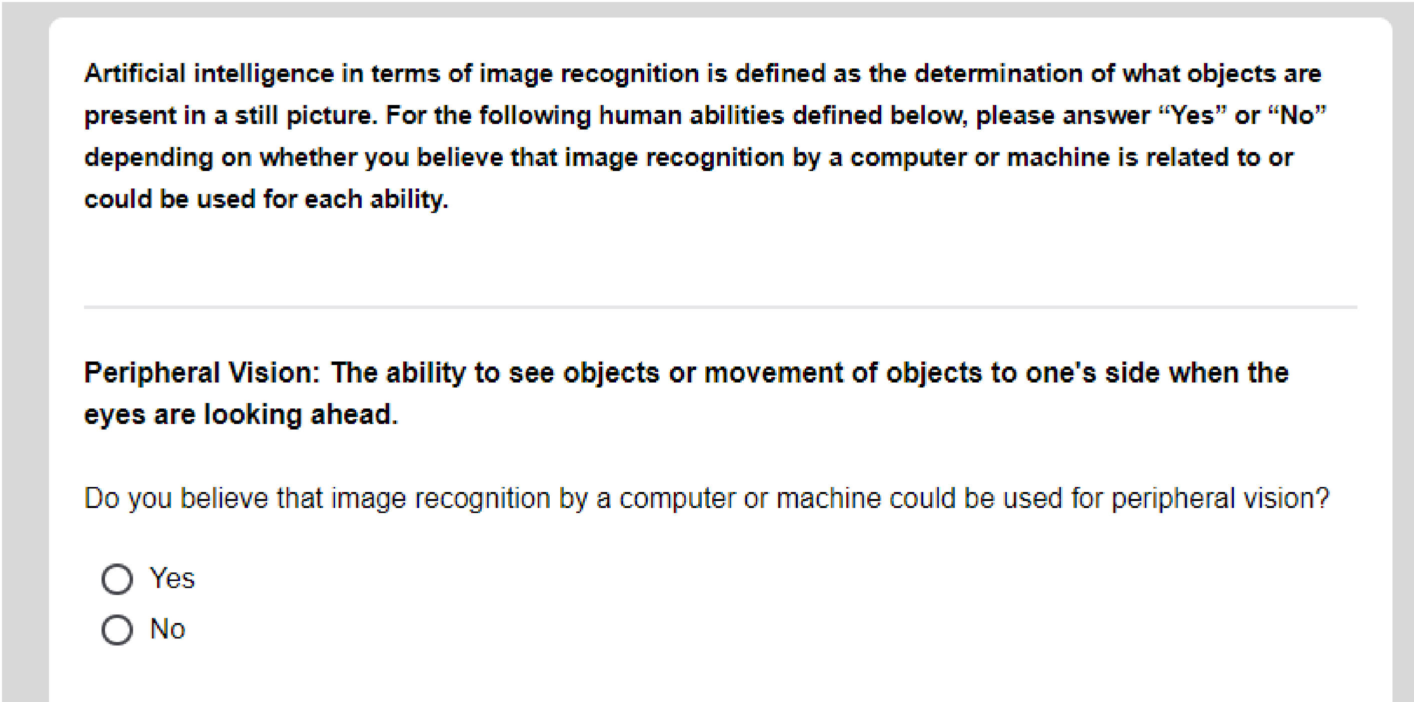
simple “Yes or No” question for simplicity and to limit the extent to which participants can express their own biases about the relationship between AI and the ability because our measure is designed to be agnostic as to whether AI is a complement to or a substitute for labor.

We acknowledge that this crowdsourced approach has weaknesses. Respondents’ perceptions of relatedness may be affected by observed progress on different applications thus far, as well as by lay understandings of how AI technologies can be used in the workplace. Accordingly, they may not recognize or anticipate creative or unconventional ways in which different AI applications might affect certain abilities. Nevertheless, we believe that the responses do provide us with a means to measure the relationship between different AI applications and occupational abilities. An example of a question used for “image recognition” is presented in *Appendix Figure A1*.

Respondents receive \$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 each 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 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 ten separate EFF AI applications to the 52 O*NET occupational abilities.

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: Discussion of the AIOE Scores for Truck Drivers and Taxi Drivers

Media, policymakers, and researchers appear to be particularly concerned about some occupations that may be negatively affected by advances in AI. For example, AI technologies have shown the potential to outperform radiologists in detecting some abnormalities in x-rays, which has led to much debate over how AI may affect 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 database used in the construction of the AIOE measures does not contain data on workplace abilities required by radiologists specifically;[2] instead we focus on two other occupations that are also 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 the form 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 (Murphy 2017, Rea et al. 2017).

Despite these concerns, long-haul truck drivers and taxi drivers do not receive particularly high AIOE measures. Long-haul truck drivers have an AIOE measure at the 14th percentile in relation to all other occupations in our sample, while taxi drivers and chauffeurs are at the 34th percentile. In some respects, this may seem surprising. Both occupations require some abilities that are highly exposed to 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 AIOE

[2] The occupations of radiation therapist and radiation technologist are related but require different abilities and entail performing quite different tasks.

measures for the occupations may be driven in part by our decision to focus on the exposure to just AI technologies instead of robotics, sensors, and other technologies.

While the AIOE captures the exposure of occupational abilities and tasks to AI technologies, by design it does not capture advances in robotics technologies. Autonomous vehicles integrate AI technologies, but the driving component itself relies on robotics. Thus, although the AIOE can capture how certain abilities used by truck and taxi drivers are exposed to advances in AI (e.g., the cognitive abilities required to construct a route, the 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 relates to abilities or occupations (e.g., the transition from the AI to the physical actions taken to actually turn a steering wheel and drive a vehicle). Given the large role that physical manipulation and robotics technologies currently have in these occupations, the AIOE suggests that AI itself is unlikely to have an outsized influence on these occupations.

In comparing the two occupations, one may then wonder why taxi drivers are considered to have higher exposure to AI than the long-haul truck drivers. As with the example of surgeons and slaughterhouse workers, the difference is accounted for by the abilities that do not overlap between the two occupations. At least as of now, O*NET suggests that taxi drivers rely more heavily on a number of cognitive and sensory skills that AI may be related to, such as oral comprehension or time sharing (i.e., the ability to shift back and forth between two or more activities or sources of information). Because such abilities are more heavily weighted for taxi drivers than for long-haul truckers, taxi drivers are considered relatively more exposed to AI.

This raises an important facet of our measure as constructed: it is reliant on accurate depictions of the abilities needed within an occupation and does not account for potential changes in occupational abilities based on advances in technologies. It is possible that, in the future, technological advances will alter whether and how certain abilities are used within an occupation. For example, perhaps the cognitive abilities considered important for taxi drivers now, such as oral comprehension and speech recognition, might become less important in the future if individuals are able to enter their destination using ride-sharing applications or if traditional taxis are replaced by self-driving cars. If that is the case, we may over- or underestimate the relative occupational exposure to AI based on outdated information regarding occupational abilities. However, this approach lets us avoid making assumptions about whether or how AI changes the required abilities or task composition of an occupation. Further, our methodology allows for the AIOE measure to be updated as O*NET releases new updates, providing us with an opportunity to reconstruct measures of AI exposure as the composition of abilities within occupations shifts.

Appendix C: Quantitative Validation of the AIOE and Related Measures

In addition to our qualitative review of occupations and their AIOE measures, we test the robustness of our AIOE measure and seek to validate the measure quantitatively. To do so, we test the robustness of our measure along four separate dimensions: (1) we consider the construction of our matrix linking AI applications to occupational abilities, (2) we test the sensitivity of the measure to which set of AI applications is included, (3) we use job postings to measure the correlation between the AIOE measure and the use of AI skills within an occupation, and (4) we examine how changes in occupational definitions by O*NET affect the AIOE measure over time.

C.1 Robustness of the Application-Ability Matrix

One key component of our methodology is the matrix constructed using mTurk survey data to connect progress in the ten EFF AI applications with the 52 O*NET abilities. In the process of conducting the surveys to construct this matrix, we collect Amazon-provided data on the educational backgrounds of survey respondents. To determine whether our application-ability relatedness scores might be biased by including laypeople without expertise in the phenomenon, 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 whose highest degree was in computer science or engineering. The correlations across the different samples are broken down by EFF AI application in *Appendix Table C1* and by O*NET ability in *Appendix Table C2*.

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 (we find that the median correlations between our full-sample application-ability relatedness scores and the corresponding scores are 0.98 and 0.94 at the AI application level and 0.97 and 0.92 at the occupation ability level for the graduate degree and computer science and engineering subsamples respectively). These findings suggest that the AIOE measures 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 understanding of AI technologies.

To further explore this, we constructed an alternative version of our application-ability matrix with the help of a focus group of four computer scientists who conduct research on AI and digital technologies. Although the focus group is small, it consists of subject matter experts who we can expect to have a good understanding of which abilities may be more or less affected by different applications of AI. We use this alternative matrix to construct a version of the AIOE and compare it with the AIOE obtained using the mTurk-constructed matrix. The AIOE measures obtained using the expert-constructed matrix have a strong, positive relationship with the AIOE measures obtained using the mTurk-constructed matrix ($\rho = 0.987$, $p < 0.001$), suggesting that our matrix linking AI applications to occupational abilities is unlikely to be biased by its reliance on a broad sample of non-experts.

C.2 Sensitivity to Application Selection

In the construction of the AIOE measure, we focus on ten applications of AI for which the EFF has recorded scientific activity and progress from 2010 onward. These applications are consistent with the categorizations used by other academic institutions and organizations (Association for the Advancement of Artificial Intelligence (AAAI) 2021, Papers with Code 2021, Perrault et al. 2019), private firms such as the McKinsey, Deloitte, and Forrester Research, as well as scholars (Bessen et al. 2018, Martínez-Plumed et al. 2020), and our conversations with subject matter experts lead us to believe that they represent fundamental applications of AI that are likely to cover the most common and likely uses of AI (at least in the medium run). However, there are reasons to be concerned that using this select set of applications could bias our results. Our methodology treats each application of AI as independent since accounting for the various interdependencies would be intractable. Accounting for the relationship between different applications of AI represents a significant challenge as it is often difficult to draw clear lines between applications that reflect similar tasks. For example, one could argue that image recognition is more similar to visual question answering than to the ability to play abstract strategy games. In that sense, the selection of applications might bias our results if we were to "double count" by including applications that have overlapping uses or effects on occupational abilities. In addition, if we exclude an application that is related to a unique set of abilities relative to our considered applications, we may also neglect important ways in which occupations can be exposed to AI.

To address this issue, we conduct two robustness checks that examines the sensitivity of the AIOE measure to excluding certain applications in the construction of the measure. These checks should allow us to understand how sensitive the measure is to the selection of applications.

As a first test, we construct ten alternative versions of the AIOE, each version excluding one of the ten applications of AI we consider in our baseline AIOE measure. We then examine the correlation across these different AIOE measures; the results of this analysis are presented in *Appendix Table C3*.

Across the different measures of the AIOE constructed using different samples of AI applications, we find a strikingly high correlation. Correlations between the baseline AIOE and the alternative measures constructed to each exclude an application of AI are all greater than 0.99 (and all significant at $p < 0.001$).

As a second check, we construct alternative versions of the AIOE using the set of applications from the EFF that are most frequently referred to by other scholars and experts in AI. We first compile categorizations used by professional and industry organizations, such as the McKinsey Global Institute (Bughin et al. 2017), Forrester Research (Sridharan et al. 2020), and Deloitte (van de Gevel et al. 2017), as well as those constructed by academics, such as Bessen et al. (2018) and Martínez-Plumed et al. (2020), and academic institutions and organizations, such as Stanford's AI Index (Perrault et al. 2019), the Association for the Advancement of Artificial Intelligence (Association for the Advancement of Artificial Intelligence (AAAI) 2021), and the Papers with Code, an organization that has created a repository of research on the state-of-the-art in machine learning (Papers with Code 2021).[3] While the categorizations vary across sources, we find a high degree of correspondence across these different sources. Of the ten applications considered by the EFF, five are present in some form across the majority of considered sources: image recognition, language modeling, reading comprehension, speech recognition, and translation. Given that these applications appear to be referred to almost universally as fundamental applications of AI, we believe that they should be a good benchmark to reference the AIOE against. We compare an alternative version of the AIOE constructed with this set of applications to the AIOE constructed with the full set of ten AI applications from the EFF and find a strikingly high correlation ($r = 0.996$; $p < 0.001$).[4]

[3] For a breakdown of the applications of AI discussed in each of these sources, please see *Appendix Table C4*.
[4] Versions of the AIOE constructed either excluding language modeling and reading comprehension or including only one of them have a correlation with the baseline AIOE ranging from 0.997 to 0.999.

The high level of correlation across versions of the AIOE constructed using different samples of applications is due to the similarity in abilities exposed to AI across applications. As discussed in Sections 3.1 and 3.2 above, we find that our measure of AI exposure is highly related to the presence of cognitive and sensory abilities. While each AI application may be more or less related to certain individual abilities, we find that all AI applications are most related to cognitive or sensory abilities, and across the O*NET data, such families of abilities are often used together within an occupation. Accordingly, occupations that rely heavily on such abilities are likely to have high AIOE measures regardless of what sample of AI applications we focus on.

Again, we seem to find suggestive evidence that AI is most likely to affect cognitive and sensory abilities. This makes sense to us given that AI technologies revolve around iterative learning and excel at perception-related tasks (Raj and Seamans 2019). This check provides us with confidence that our results are unlikely to be meaningfully biased based on the sample of AI applications that we consider. Our scores are not sensitive to excluding any of the applications included in our sample and based on this test and the nature of AI technologies, we believe that any applications that we have possibly excluded are likely to also be related to a similar set of cognitive and sensory abilities.

C.3 Relationship between the AIOE and AI Skills in Job Postings

As an additional validation exercise, we evaluate the relationship between the AIOE measure and job skills using Labor Insight data from Burning Glass Technologies. The proprietary Labor Insight data from Burning Glass provide labor market information by compiling 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 the skills required for each job posting. Using this information in conjunction with machine learning analysis and qualitative research, Burning Glass classifies over 17,000 unique skills into a taxonomy of skill clusters by grouping together similar skills that are substitutable in many labor market contexts or are often taught or acquired together (Restuccia 2019).

We use the Burning Glass data to measure the relationship between 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 and the AIOE measure.[5] These clusters consist of skills that require the use of such technologies (rather than focusing on the development of the technologies) and are classified using Burning Glass's machine learning-based text analysis of job postings.[6] Presumably, if the AIOE accurately measures occupations with more exposure to AI, we should find a positive correlation between the measure and the count and prevalence of AI-related skills in an occupation. We use data from the most recent version of the Burning Glass data we have access to, covering job postings for the first seven months of 2018. For each occupation, we calculate the average count of these skills required in a job posting, the average percentage of skills listed that are AI skills, and the proportion of job postings that require at least one AI skill. We find a clear positive relationship between the AIOE and the average count of AI skills required in a job posting ($r = 0.263$; $p < 0.001$), the average percentage of AI skills within a job posting ($r = 0.234$; $p < 0.001$), and the proportion of

[5] Results are robust to only including skills within the Artificial Intelligence skill cluster.
[6] For example, skills within these three clusters include broad skills such as "Neural Networks," "Random Forests," and "Deep Learning," as well as familiarity with more specific AI tools and techniques such as "AI ChatBot," "IBM Watson," "Word2Vec," and "Vowpal."

occupational postings that require at least one AI skill ($r = 0.297$; $p < 0.001$).[7] These patterns are displayed graphically in *Appendix Figure A2*. In *Appendix Figures A3* and *A4*, we replicate the analysis by comparing our AIIE and AIGE measures to AI skills requirements in job postings at the industry and regional levels, respectively. The results are in line with those in *Appendix Figure A1* and show a significant and positive relationship between the AIIE and AIGE measures and AI skills within the industry or geography.

To further corroborate the correlation, we conduct regression analyses to identify the relationship between the AIOE and the presence of AI skills within an occupation. We regress our three measures of AI skills within an occupation on the AIOE controlling for the average count of required skills in an occupation and the average proportion of specialized skills required for an occupation. The results of this analysis, presented in *Appendix Table C5*, demonstrate that even after controlling for such factors, we find statistically significant relationships between the AIOE and the presence of occupational AI skills using both ordinary least squares (OLS) and Poisson models. As an additional robustness check, we conduct this analysis at the job posting-level as well using the most recent version of the Burning Glass data we have access to, covering job postings for the first seven months of 2018. We regress the count of AI skills in a posting, the proportion of AI skills in a posting, and a binary indicator of whether or not the posting includes at least one AI skill on the AIOE controlling for the count of required skills in a posting and the proportion of specialized skills within the posting. Again, using both OLS and Poisson models and either county and sector or state-by-sector fixed effects, we find consistent evidence of a statistically meaningful and positive relationship between the AIOE and the presence of AI skills in an occupation (presented in *Appendix Table C6*).

[7] These correlations are presented graphically in *Appendix Figure A2*.

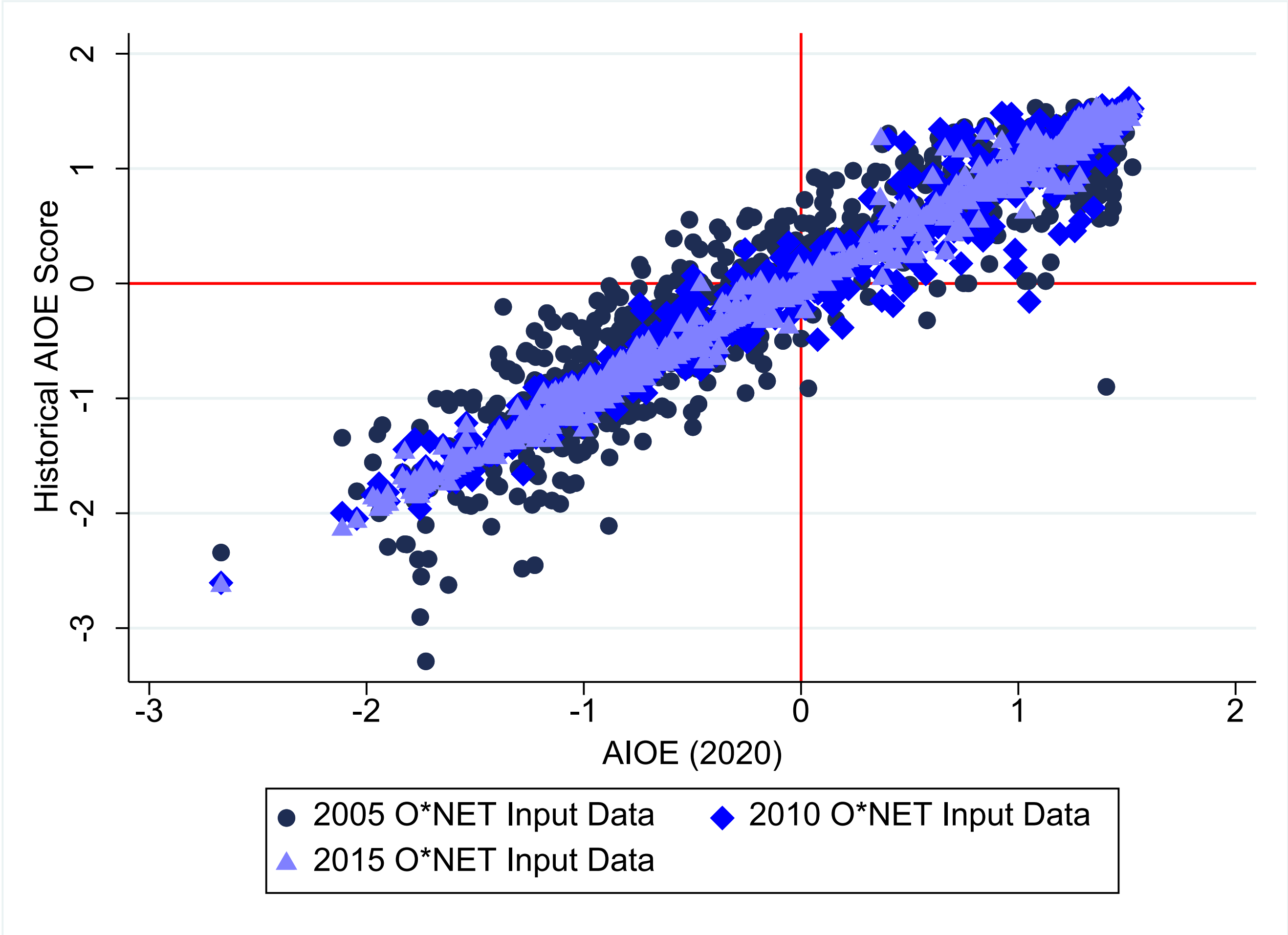
*C.4 Relationship between the AIOE and O*NET definitions over time*

As noted above, the AIOE measure is heavily reliant on accurate depictions of the abilities needed within an occupation and does not account for potential changes in occupational abilities based on advances in technologies. As occupations change over time, O*NET updates its set of occupational definitions and required abilities. To see how durable the AIOE is over time, we examine the sensitivity of the AIOE to using older versions of O*NET's occupational definitions. This test allows us to understand how quickly and to what extent changes in occupational definitions over time affect AIOE measures. Because the AIOE relies on the O*NET database as of 2020, we conduct this test by constructing historical versions of the AIOE using O*NET data from January 2015, 2010, and 2005. In *Appendix Figure C1*, we visually examine the relationship between the 2020 AIOE (x-axis) and historical versions of the AIOE constructed using O*NET input data from 2005, 2010, and 2015 (y-axis).

Figure 1 shows a strong correlation between the 2020 AIOE measure and all three of the historical versions of the AIOE. Not surprisingly, the strength of this correlation increases over time — the 2020 AIOE has a correlation of 0.911 with the 2005 AIOE, 0.982 with the 2010 AIOE, and 0.995 with the 2015 AIOE (all significant at $p < 0.001$). This test indicates that the AIOE is relatively stable over time and that occupational changes (at least in short- to medium-term time horizons) are unlikely to dramatically affect the AIOE values. We note, as occupations undergo larger changes over longer periods of time, our methodology allows for the AIOE measure to be updated as O*NET releases updates.

It is worth noting however, that using updated O*NET data may bias results due to how the demand for abilities may change for advances in AI that complement vs. substitute for occupational abilities. For abilities complemented by AI, it is likely that O*NET would note a relative increase in the demand for such abilities within occupations, making these occupations appear even more exposed than before. However, for skills that are substituted, O*NET would note a relative decrease in the demand for such abilities within an occupation, perhaps leading us to conclude that the occupation is less exposed than before. This is a limitation that is likely to exist in any setting that relies on abilities or skills to describe occupations over time. We encourage potential users of the measure to keep this in mind and emphasize that our measure is a forward-looking measure of AI exposure based on the occupational definitions at a given point in time.

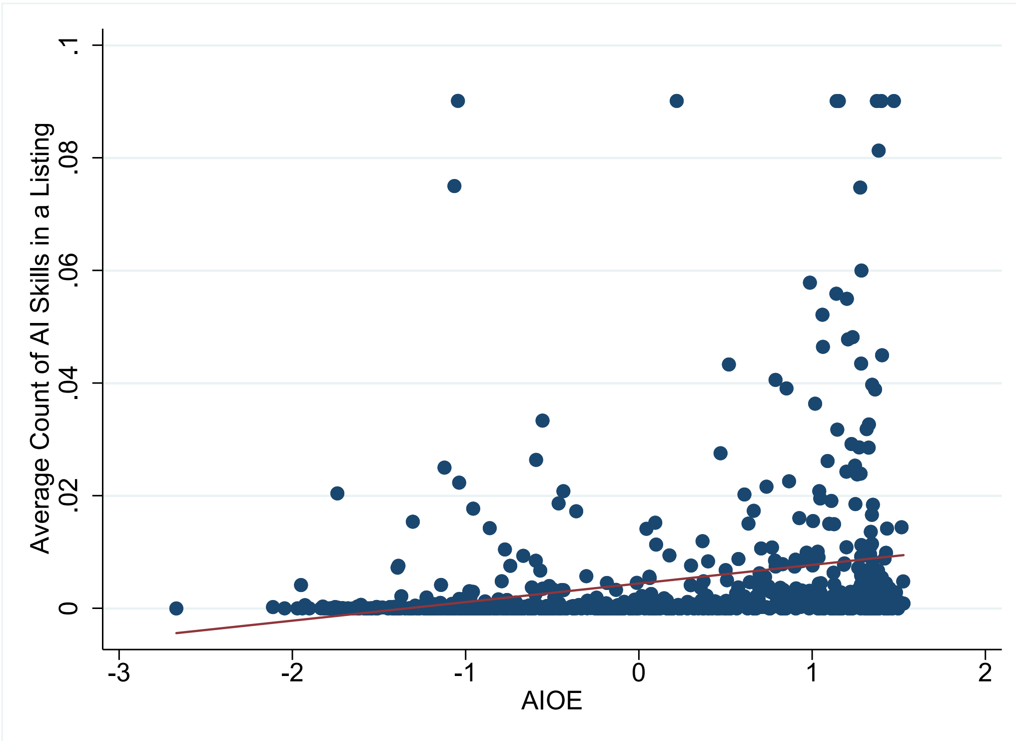
Appendix Figure C1: AIOE with Historical O*NET Input Data



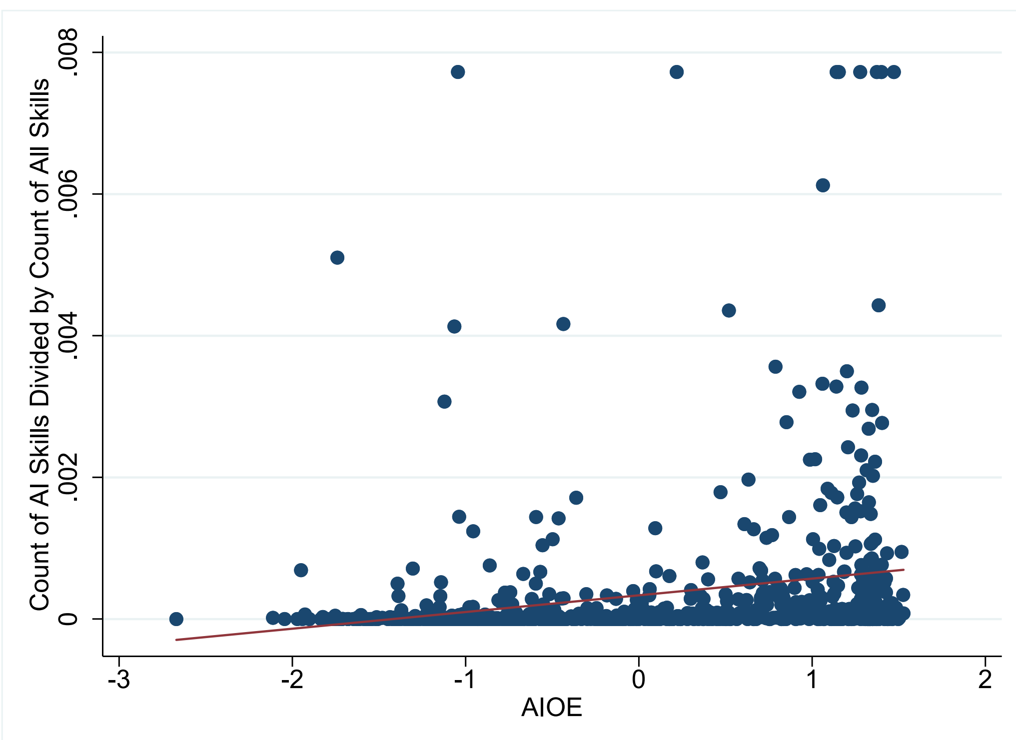
Note: The *x*-axis displays the standardized AIOE using O*NET data on occupational abilities as of January 2020. The charted series represent historical versions of the AIOE using O*NET occupational ability data as of January 2005, 2010, and 2015. Only occupations that have a 2020 AIOE are included in this figure.

Figure C2: Correlation between AIOE and Occupation AI Skills

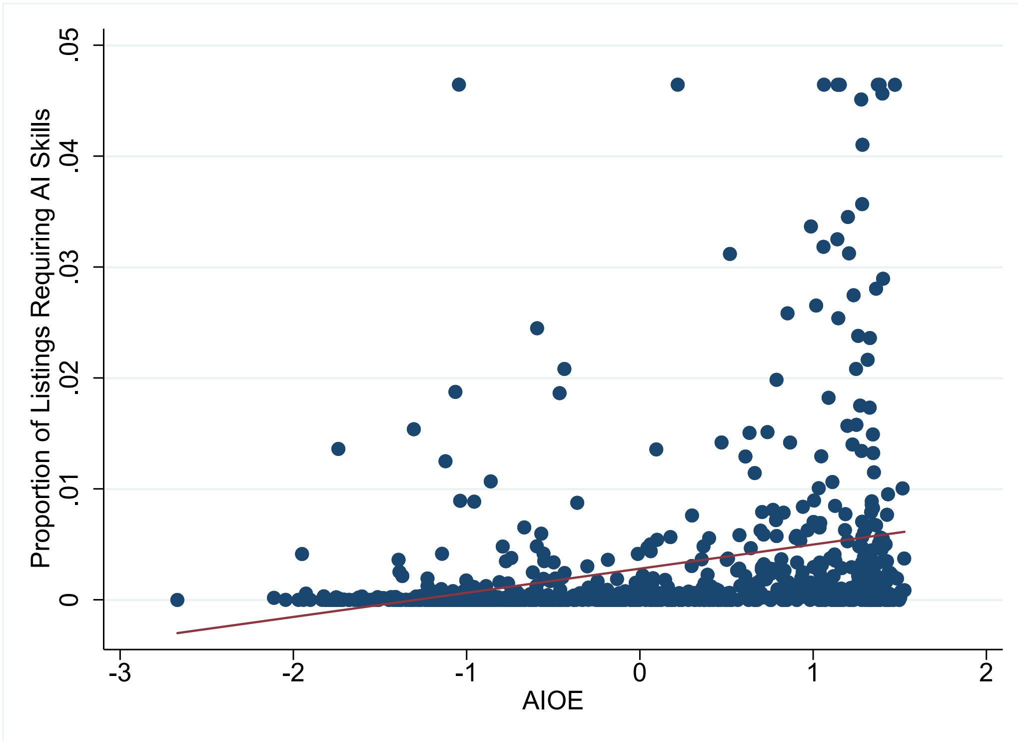
Panel A. AIOE and the Average Count of AI Skills Required in a Job Posting.



Panel B. AIOE and the Average Percentage of AI Skills Required in a Job Posting.



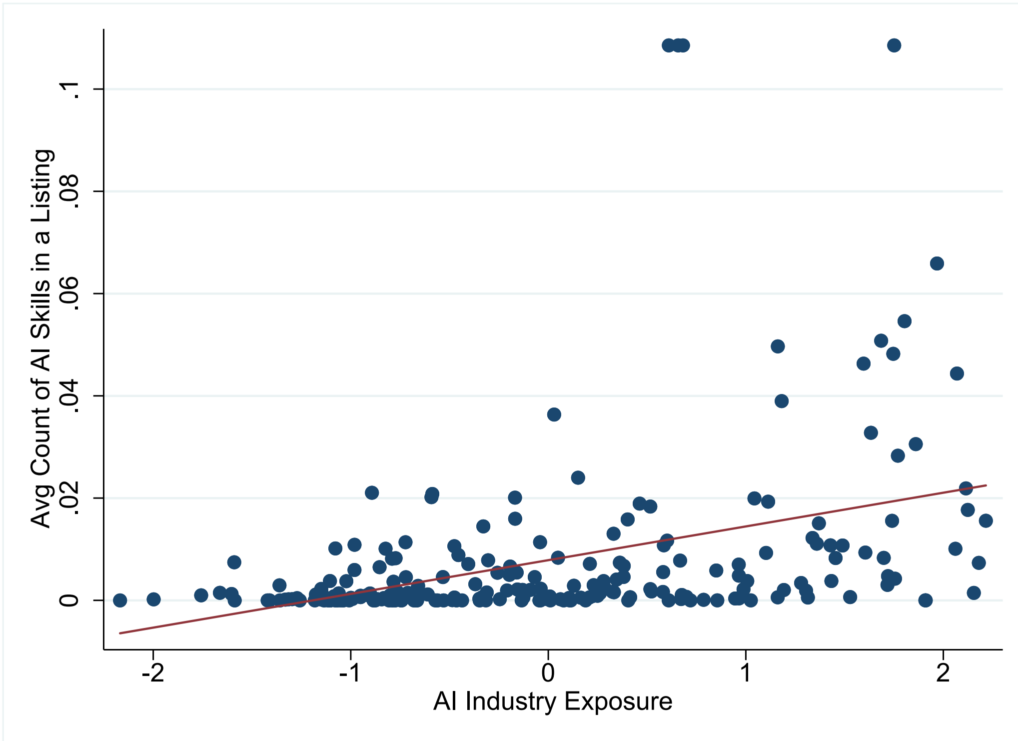
Panel C. AIOE and the Proportion of Job Postings Requiring AI Skills.



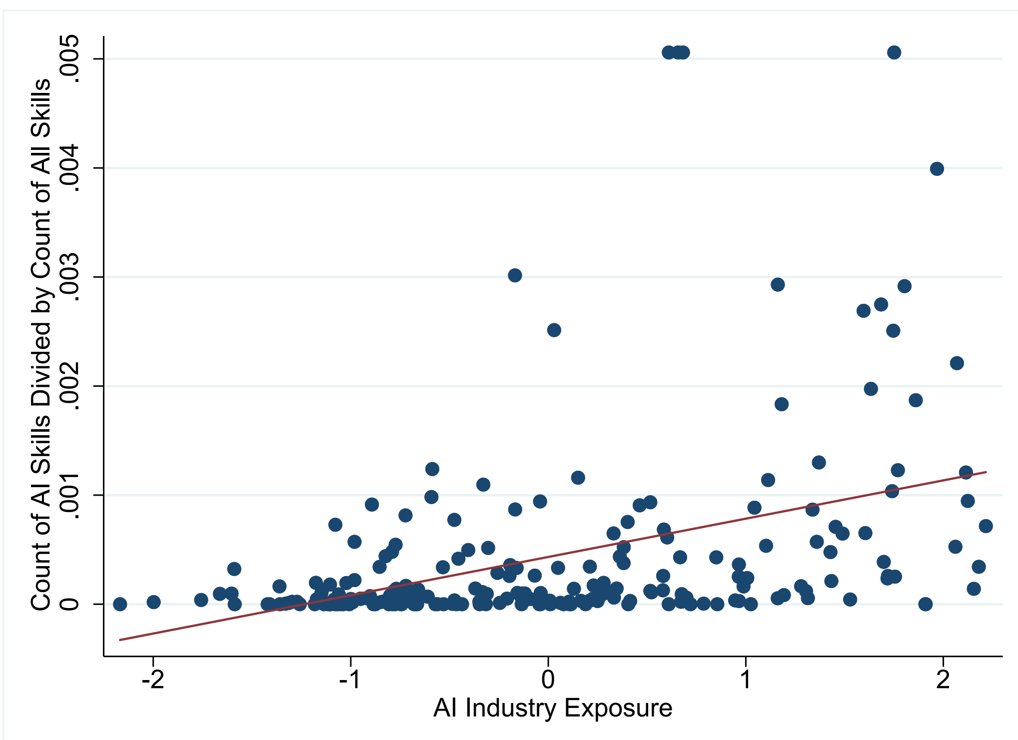
Note: Data on AI skills within occupations come from Burning Glass Technologies Labor Insight data. AI skills include all skills within the artificial intelligence, machine learning, or natural language processing families. Burning Glass provides data on online job postings and uses machine learning technologies to classify required skills. AI skills refers to the use of AI technologies, not to their development. Data are from job postings in 2018 (January through July inclusive), the most recent Burning Glass data accessible to the authors at the time of writing.

Appendix Figure C3: Correlation between AIIE and Industry Occupation AI Skills

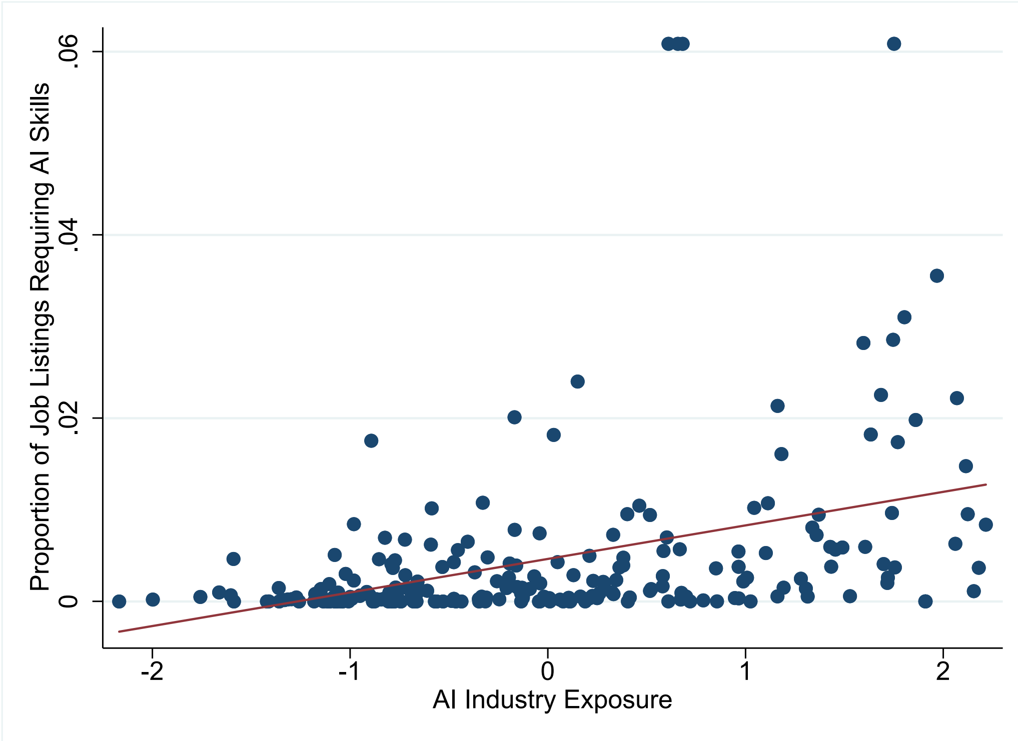
Panel A. AIIE and the Average Count of AI Skills Required for an Industry Posting.



Panel B. AIOE and the Average Percentage of AI Skills Required in an Industry Posting.



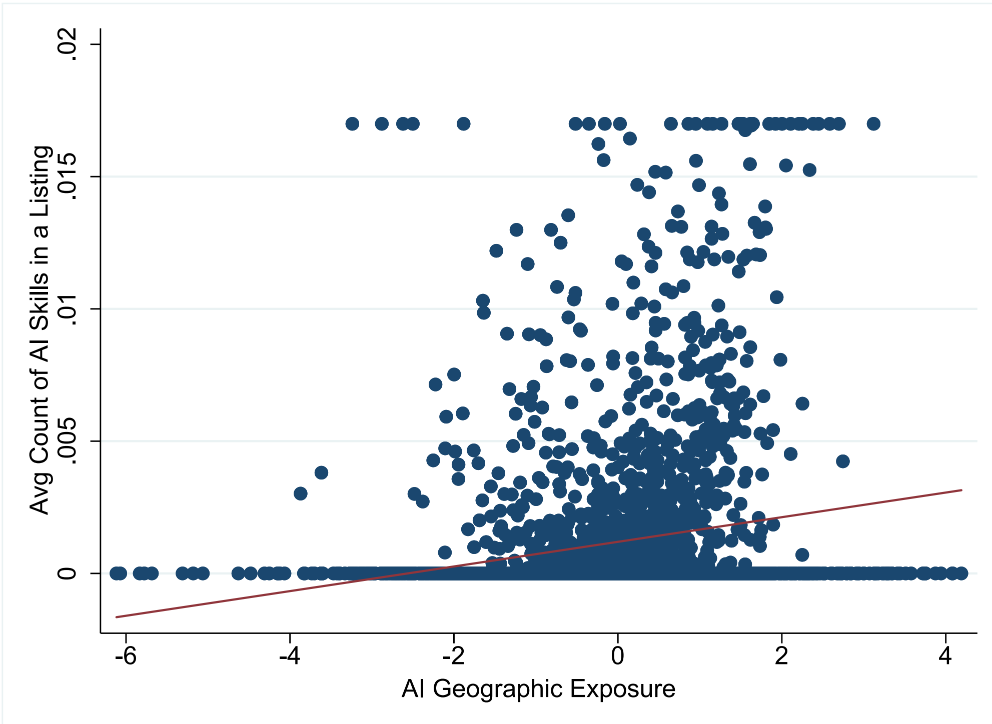
Panel C. AIIE and the Proportion of Industry Postings Requiring AI Skills.



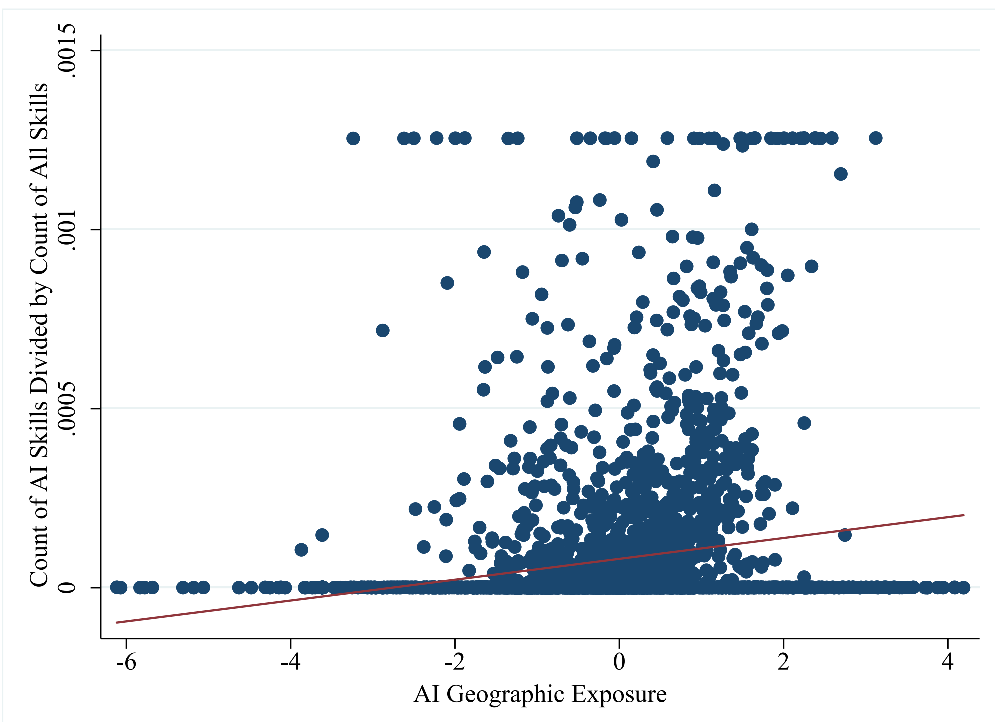
Note: Data on AI skills within occupations come from Burning Glass Technologies Labor Insight data. AI skills include all skills within the artificial intelligence, machine learning, or natural language processing families. Burning Glass provides data on online job postings and uses machine learning technologies to classify required skills. AI skills refers to the use of AI technologies, not to their development. Data are from job postings in 2018 (January through July inclusive), the most recent Burning Glass data accessible to the authors at the time of writing.

Appendix Figure C4: Correlation between AIGE and Within-County Occupation AI Skills

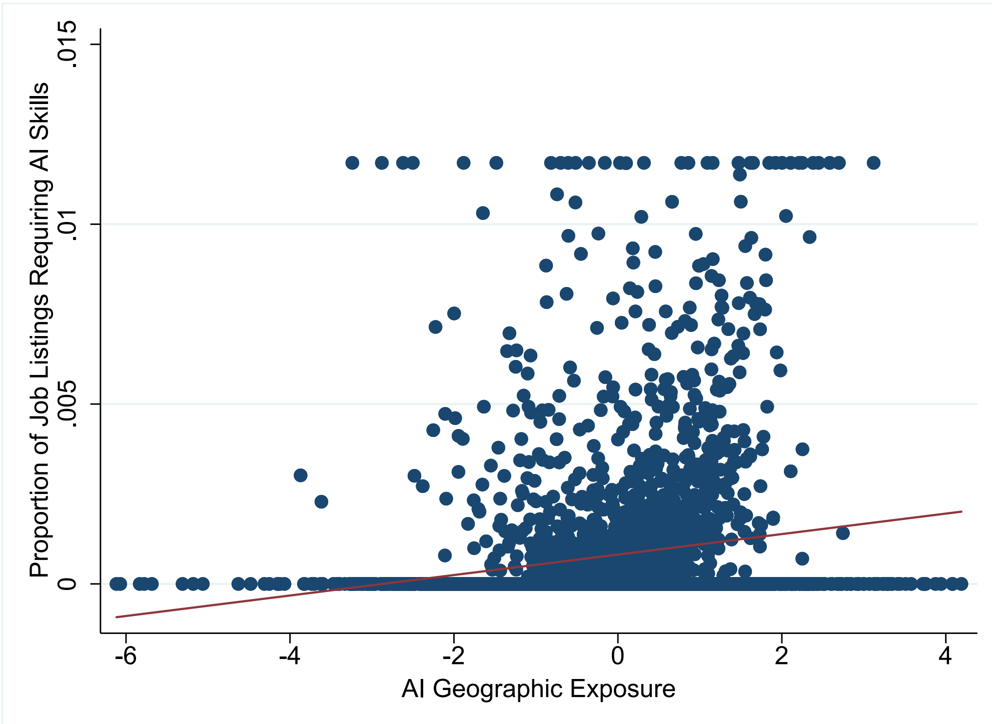
Panel A. AIGE and the Average Count of AI Skills Required for Within-County Postings.



Panel B. AIGE and the Average Percentage of AI Skills Required for Within-County Postings.



Panel C. AIGE and the Proportion of Within-County Postings Requiring AI Skills.



Note: Data on AI skills within occupations come from Burning Glass Technologies Labor Insight data. AI skills include all skills within the artificial intelligence, machine learning, or natural language processing families. Burning Glass provides data on online job postings and uses machine learning technologies to classify required skills. AI Skills refers to the use of AI technologies, not to their development. Data are from job postings in 2018 (January through July inclusive), the most recent Burning Glass data accessible to the authors at the time of writing.

Appendix Table C1: Correlation Coefficients across mTurk Subsamples by EFF AI Application

	Correlation Coefficient between the 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 AI applications with O*NET abilities.

Appendix Table C2: Correlation Coefficients across mTurk Subsamples by O*NET Ability

	Correlation Coefficient between the Subsample and the Full Sample	
O*NET Abilities	**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 AI applications with O*NET abilities.

Appendix Table C3: Selection of AI Applications

	Baseline AIOE measure	*AIOE* Excluding… Abstract Strategy Games	Real Time Video Games	Image Recognition	Visual Question Answering	Image Generation	Reading Comprehension	Language Modeling	Translation	Speech Recognition	Instrumental Track Recognition
Baseline AIOE measure	1.0000										
AIOE Excluding…											
Abstract Strategy Games	0.9998	1.0000									
Real Time Video Games	0.9996	0.9998	1.0000								
Image Recognition	0.9995	0.9998	0.9999	1.0000							
Visual Question Answering	0.9997	0.9999	0.9999	1.0000	1.0000						
Image Generation	0.9995	0.9998	0.9998	0.9999	0.9999	1.0000					
Reading Comprehension	0.9994	0.9989	0.9981	0.9981	0.9985	0.9983	1.0000				
Language Modeling	0.9989	0.9978	0.9971	0.9969	0.9974	0.9971	0.9996	1.0000			
Translation	0.9990	0.9980	0.9974	0.9972	0.9977	0.9974	0.9997	1.0000	1.0000		
Speech Recognition	0.9995	0.9986	0.9983	0.9980	0.9984	0.9980	0.9995	0.9998	0.9998	1.0000	
Instrumental Track Recognition	0.9998	0.9994	0.9994	0.9992	0.9994	0.9991	0.9989	0.9987	0.9989	0.9995	1.0000

Note: Table presents a correlation matrix displaying the relationship between different variations of the AIOE constructed using different samples of AI applications. The Baseline AIOE measure uses the ten EFF AI applications described in Table 1. The variations are constructed by excluding a single application. All correlations are significant at $p < 0.001$.

Appendix Table C4: Applications of AI Across Sources

Source	Type of Source	AI Categories
Bughin JR, Hazan E, Ramaswamy S, Chui M, Allas T, Peter D, Henke N, Trench M (2017) *Artificial Intelligence: The Next Digital Frontier* (McKinsey Global Institute).	Industry	Decision management, image recognition and video processing, machine learning and deep learning, natural language generation, speech recognition, virtual agents or artificial conversational entities.
Sridharan S, Leganza G, Vale J (2020) *Research Overview: Artificial Intelligence* (Forrester Research).	Industry	AI-optimized hardware, biometrics, decision management, deep learning platforms, machine learning platforms, natural language generation, natural language processing, robot process automation, speech recognition, virtual agents.
van de Gevel J, Broersen S, Wolvius C (2017) Applications of Artificial Intelligence. *Deloitte*. Retrieved (February 4, 2021), https://www2.deloitte.com/se/sv/pages/technology/articles/part3-applications-of-artificial-intelligence.html.	Industry	Image recognition, games, Q&A, speech recognition, translation.
Association for the Advancement of Artificial Intelligence (AAAI) (2021) AITopics. Association for the Advancement of Artificial Intelligence (AAAI). Retrieved (February 25, 2021), https://aitopics.org/search.	Academic	Assistive technologies, challenges, cognitive science, games, history, human-centered computing, issues, machine learning, natural language, representation and reasoning, robots, science fiction, speech, systems and languages, the future, vision.
Bessen JE, Impink SM, Reichensperger L, Seamans R (2018) *The Business of AI Startups* (Social Science Research Network, Rochester, NY).	Academic	Decision management, natural language classification, natural language generation, natural language translation, natural language understanding and text analysis, robotic process automation, sentiment/emotion analysis, speech recognition, virtual agents/chatbots, visual recognition.
Martínez-Plumed F, Tolan S, Pesole A, Hernández-Orallo J, Fernández-Macías E, Gómez E (2020) Does AI Qualify for the Job?: A Bidirectional Model Mapping Labour and AI Intensities. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society*. (ACM, New York NY USA), 94–100.	Academic	Automated vehicles, computer vision, game playing, information retrieval, machine translation, music analysis, prediction, robotic navigation and interaction, speech recognition, text summarization.
Papers with Code (2021) Browse State-of-the-Art. *Papers with Code*. Retrieved (February 25, 2021), https://paperswithcode.com/sota.	Academic	Adversarial, audio, computer vision, medical, music, natural language processing, playing games, reasoning, robots, speech.
Perrault CR, Shoham Y, Brynjolfsson E, Clark J, Etchemendy J, Grosz B, Lyons T, Manyika J, Mishra S, Niebles JC (2019) *The AI Index 2019 Annual Report* (AI Index Steering Committee, Human-Centered AI Institute, Stanford University).	Academic	Activity recognition in video, human-level performance milestones, image classification, image generation, natural language understanding, semantic segmentation, visual question answer.

Note: Table contains sources used to identify various categorizations of applications of AI.

Appendix Table C5: AIOE and Occupation-Level AI Skills

	(1)	(2)	(3)	(4)	(5)	(6)
	Average Count of AI Skills		Average Percent AI Skills		Proportion of Postings Requiring AI Skills	
	OLS	Poisson	OLS	Poisson	OLS	Poisson
AIOE	0.001	0.470	0.010	0.504	0.001	0.525
	(0.000)	(0.159)	(0.004)	(0.185)	(0.000)	(0.145)
Average Count of Skills	0.001	0.234	0.009	0.183	0.001	0.231
	(0.000)	(0.027)	(0.002)	(0.033)	(0.000)	(0.027)
Average Proportion of Specialized Skills	0.006	1.716	0.049	1.824	0.004	1.714
	(0.003)	(0.823)	(0.023)	(0.876)	(0.002)	(0.760)
Observations	772	772	772	772	772	772
R-squared or Pseudo R-squared	0.170	0.100	0.108	0.112	0.197	0.096

Note: This table presents the results of regression analysis estimating the relationship between the AIOE and the presence of AI skills at the occupation-level. The sample includes all occupations with a constructed AIOE measure using O*NET input data from 2020. The Average Count of AI Skills is the average count of skills required for occupational job postings that are classified as AI skills, the Percent AI skills measures the average count of required AI skills divided by the total count of required skills for occupational job postings, and Proportion of Postings Requiring AI Skills is the proportion of occupational job postings that require at least one AI skill. AI skills are defined as skills within the Artificial Intelligence, Machine Learning, or Natural Language Processing skill clusters as defined by Burning Glass Technologies. We control for the average total count of required skills in a job posting and the average proportion of required specialized skills over total required skills as classified by Burning Glass Technologies. Standard errors clustered at the occupation-level are displayed in parentheses.

Appendix Table C6: AIOE and Posting-Level AI Skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Count of AI Skills				Percent AI Skills				Any AI Skills in Occupation			
	OLS	Poisson	OLS	Poisson	OLS	Poisson	OLS	Poisson	OLS	Poisson	OLS	Poisson
AIOE	0.0017	1.2827	0.0022	1.3852	0.0003	1.2220	0.0003	1.3426	0.0014	1.2591	0.0017	1.3529
	(0.0008)	(0.2126)	(0.0009)	(0.2148)	(0.0001)	(0.2010)	(0.0001)	(0.2054)	(0.0005)	(0.1730)	(0.0005)	(0.1758)
Count of Skills	0.0018	0.0340	0.0019	0.0380	0.0000	0.0269	0.0000	0.0300	0.0009	0.0331	0.0009	0.0365
	(0.0005)	(0.0010)	(0.0005)	(0.0012)	(0.0000)	(0.0015)	(0.0000)	(0.0018)	(0.0002)	(0.0010)	(0.0002)	(0.0010)
Proportion Specialized Skills	0.0188	4.2163	0.0194	4.3406	0.0012	4.2671	0.0013	4.4085	0.0101	3.6474	0.0104	3.7623
	(0.0061)	(0.2956)	(0.0063)	(0.2898)	(0.0004)	(0.3093)	(0.0004)	(0.3018)	(0.0030)	(0.2392)	(0.0032)	(0.2422)
County FEs?	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Sector FEs?	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Sector X State FEs?	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	14,689,878	13,266,255	14,877,546	14,290,025	14,689,878	13,266,255	14,877,546	14,290,025	14,689,878	13,266,255	14,877,546	14,290,025
R-squared or Pseudo R-squared	0.0169	0.2400	0.0155	0.2317	0.0100	0.1646	0.0081	0.1542	0.0210	0.2092	0.0193	0.2023

Note: This table presents the results of regression analysis estimating the relationship between the AIOE and the presence of AI skills at the job-posting-level. The sample includes all job postings within the Burning Glass data for January through July 2018 (the latest version of the data available to the authors). The Count of AI Skills is the count of skills required for the job posting classified as AI skills, the Percent AI skills measures the count of required AI skills divided by the total count of required skills, and Any AI Skills in Occupation is a binary variable that takes the value of one if the job posting requires any AI skills. AI skills are defined as skills within the Artificial Intelligence, Machine Learning, or Natural Language Processing skill clusters as defined by Burning Glass Technologies. We control for the total count of required skills in a job posting and the proportion of required specialized skills over total required skills as classified by Burning Glass Technologies. Standard errors clustered at the occupation-level are displayed in parentheses.

Appendix D: Comparing the AIOE to Other Existing Datasets

Other researchers have created datasets to measure the exposure to and impact of AI on occupations and industries. In this section, we briefly review them before explaining how our dataset is unique.

D.1 Other Existing Datasets

One notable study attempting to link occupations to AI technologies was undertaken by Frey and Osborne (2017). The authors work with a group of experts to forecast what job tasks may be particularly susceptible to automation. 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, noting potential engineering bottlenecks for 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 occupations, creating a measure for how susceptible to automation each occupation is.

A similar, task-based approach was undertaken by Brynjolfsson, Mitchell, and Rock (2018) and Brynjolfsson et al. (2020). Brynjolfsson and co-authors construct a rubric to ascertain how "suitable for machine learning" different workplace activities are, and then use a crowdsourcing service to apply this rubric to the full range of work activities outlined by the Bureau of Labor Statistics. They aggregate these to the occupation level to quantify the extent to which tasks within an occupation are suitable for machine learning. In addition, Brynjolfsson and co-authors (2020) present an estimate of the annual wage bill susceptible to exposure by two-digit NAICS industry, providing some sense of industry exposure to AI.

Other studies have used patent data to study the relationship between AI and labor. Mann and Püttmann (2017) 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 and geographies they are likely to be used in and find that, although automation causes manufacturing employment to fall, it increases employment in the service sector and overall has a positive impact on employment. Mann and Püttmann (2017) also use a similar methodology to construct a measure of available automation technology at the three-digit SIC level, and find that the number of automation patents is positively related to investment in computer capital and robot shipments. Webb (2020) similarly uses a machine learning algorithm to identify which tasks are most likely to be automated by AI, and suggests that high-skill tasks and occupations will be particularly affected by advances in AI technology.

Several other reports by private firms and research institutes attempt to identify which industries are more or less affected by advances AI technology. Using Webb's (2020) occupation-level exposure scores, the Brookings Institution published a report that constructed industry-level exposure to AI automation in which it suggests that the advancement of AI technology is highest among primary and secondary industries such as manufacturing, agriculture, and resource extraction (Muro et al. 2019). The McKinsey Global Institute released a report that estimated the potential value of AI by sector based on internal models of the relative effectiveness of AI in comparison with existing technologies and the potential use cases across industries (Chui et al. 2018). Similarly, Accenture estimated the potential gains to industry profit from advances in AI technology using a methodology that links the probability of automation at the occupation level to improvements in AI over time and to total factor productivity data across industries (Purdy and Daugherty 2017). While these reports provide useful context and are a valuable resource given the nascent state of the field, they provide limited visibility into the methodology used to calculate the results and produce proprietary data that are difficult to access and therefore of limited use.

D.2 Distinctions between the AIOE and Existing Datasets

The studies outlined above make important contributions to what is a nascent effort to understand the effect of AI on labor and occupations. However, we believe that our measure has unique features and strengths. First, our methodology considers specific applications of AI (e.g., image recognition, speech recognition, and others) and links them to workplace abilities and then to occupations, industries, and geographies. Several of the existing measures consider the effect of automation (Frey and Osborne 2017, Mann and Püttmann 2017) on labor, without specifying whether automation occurs via AI, robots, sensors, or another type of technology. And even measures that specifically consider the effect of AI or machine learning on labor (Brynjolfsson et al. 2018, 2020, Webb 2020) do not discern between specific applications of AI.

Second, our measure identifies the relative *exposure* to AI but remains agnostic as to whether AI complements or substitutes for tasks and labor. In contrast, many of the other measures (e.g., Brynjolfsson et al. 2020, Frey and Osborne 2017, Webb 2020) are focused on the potential for new technologies to substitute for or automate occupations or tasks. To be sure, substitution may well occur in many cases. But we believe it is important to be able to empirically study conditions under which exposure to AI will substitute for or complement labor, especially as we still do not yet know whether or how AI will affect labor markets.

Third, our approach provides a snapshot of occupational exposure to AI based on the current nature of occupations. While other measures use forward-looking approaches that rely on expert projections or crowdsourced evaluations to identify which tasks may be suitable to AI or automation or how the task composition of an occupation may change as it is affected by AI (Brynjolfsson et al. 2018, 2020, Frey and Osborne 2017), we consider the task composition of an occupation as fixed in our analysis based on the O*NET occupation data. While this prevents us from predicting how task composition and skill content of occupations change over time, it provides us with an accurate representation of AI exposure in the present and allows us to update our measure moving forward as the abilities and skills required within occupations change. Further, it allows us to avoid making assumptions about how AI will affect different occupational tasks (consistent with our agnostic approach to whether AI substitutes for labor).

These different approaches are complementary and can be useful to different researchers depending on the specific questions being asked. Below we discuss in more detail potential applications of the AIOE, AIIE, and AIGE measures.