Collaborative Robots in the Workplace: Occupational, Geographic, and Demographic Opportunities for Technology Adoption

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Abstract: Collaborative robots, or "cobots," represent a growing share of industrial robots and have the potential to boost productivity, enhance workplace flexibility, and improve working conditions across a wide range of industries. Drawing on expert assessments of cobot capabilities and detailed occupational task data from O*NET, we develop the Cobot Adoption Potential Index (CAPI), a measure of the technical potential for cobot integration across occupations. We link CAPI to data from the American Community Survey (ACS) and the Bureau of Labor Statistics (BLS) to characterize the demographic composition of workers in high-potential occupations and to identify the industries and regions where these occupations are concentrated. Workers in these occupations tend to be younger on average, but cobot technology may also expand opportunities for older workers and those with work-related disabilities. These results provide a basis for targeting policies—such as training and workforce development programs—to the workers and locations most likely to be affected. Finally, we document that high-CAPI occupations currently exhibit elevated workplace injury rates, highlighting opportunities for cobots to contribute to improved occupational safety.

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1. Introduction and Related Literature

New robotic technologies hold significant potential for improving worker productivity and working conditions (Schmidtler et al., 2015). In this paper, we focus on one emerging technology: collaborative robots. Collaborative robots, or "cobots," are robotic technologies designed to work alongside people and offer flexible, safe, and user-friendly automation in manual tasks (Vicentini, 2021). The cobot market share is projected to grow by nearly 30% in the U.S. and 32% globally by 2030 (Grand View Research, 2023), which calls for an understanding where cobots can be integrated and what their impacts may be.

Using detailed occupational task data from O*NET and expert assessments of cobot compatibility for selected occupations (Liu et al., 2022), we develop the *Cobot Adoption Potential Index* (*CAPI*). CAPI provides a measure of the technical potential for cobot integration across occupations and serves as a tool for researchers and practitioners to identify where cobots could be most effectively deployed. Importantly, this index reflects not only where cobots *can* be adopted but also how they might transform the nature of work within those occupations. Cobots, like other forms of automation, are most compatible with occupations characterized by repetitive, physical tasks. However, unlike traditional industrial robots, cobots have substantial potential outside of manufacturing, with particular relevance for service-intensive sectors such as hospitality and agriculture.

We illustrate the use of CAPI through three applications. First, we link CAPI to detailed regional data from the Bureau of Labor Statistics (BLS) to estimate where cobots are most likely to be adopted, helping managers anticipate local competitive pressures. Second, we analyze the demographic composition of workers in high-potential occupations using the American Community Survey (ACS) to assess how easily the current workforce can adapt to cobot adoption. Because successful cobot deployment depends on worker collaboration, understanding workforce adaptability is essential. Finally, we examine workplace injury data and show that occupations with high CAPI scores also have elevated injury rates, highlighting an opportunity for cobots to improve workplace safety by reducing exposure to high-risk tasks. This has the additional potential of both reducing employment costs and making jobs more appealing.

Geographically, we find that cobot adoption potential is broad, but relatively more concentrated in several areas of the southeastern and western United States. Demographically, workers in high-CAPI occupations tend to be younger on average, which may facilitate skill acquisition and technology adoption, but they also tend to have lower levels of formal education, suggesting a need for targeted training interventions. Taken together, these results can inform policy design and workforce development efforts aimed at maximizing the benefits of cobot technology while minimizing potential disruption.

The state of cobot technology and potential for integration. Unlike traditional robotic automation, which often minimizes or eliminates human interaction, cobots are explicitly designed for collaborative configurations (Pearce et al., 2018). Their relative affordability, re-configurability, and do-it-yourself (DIY) installation options make them more accessible than conventional robotic systems that typically require specialized expertise for safe integration (Magalhaes and Ferreira, 2022; Brettel et al., 2014).

Prior work has examined the technical and organizational conditions under which cobots can be integrated into manual processes, identifying both opportunities and barriers (Ponda et al., 2010; Pearce et al., 2018; Casalino et al., 2019; Bogner et al., 2018; Pupa and Secchi, 2021; Zhang et al., 2022; Schoen et al., 2020). We build on this literature by consolidating multiple dimensions of cobot technological capacity into a single index that allows for systematic assessment of cobot feasibility at the occupation level across the U.S.

While cobots are seen as a safe, flexible, and relatively low-cost alternative to full automation (Michaelis et al., 2020), their collaborative nature requires additional investments in worker training to ensure proper use, reconfiguration, and troubleshooting (Michaelis et al., 2020; Moffat and Gray, 2015). Where cobots can best complement human work, and how workers adapt to collaborative workflows, remain important open questions. Our contribution is to provide a tool—the CAPI—that enables researchers, managers, and policymakers to systematically evaluate where cobot adoption is technically feasible, who the affected workers are, and what strategic or policy considerations should follow.

Automation vs. augmentation. The introduction of new technologies has sparked a long-running debate about whether they primarily automate and substitute for human labor or augment it by complementing human skills. CAPI is designed with the augmentation perspective in mind: occupations that are already highly automatable receive *lower* CAPI scores, reflecting the idea that cobots are less relevant where full automation is technically feasible (Bennett, 2020).

We emphasize that CAPI provides an upper bound on the potential for cobot adoption. Indeed, work by Arntz et al. (2017); Autor and Handel (2013) and others show that estimates of replacement based on average occupational tasks are likely to overestimate displacement, owing to, among other things, task composition and variation of tasks even within narrowly defined occupations. Over time, cobots may change the task composition of occupations, shifting them toward less physically demanding, more supervisory, and decision-oriented roles. Depending on productivity gains, this could either reduce employment in some occupations or expand it if output growth is sufficiently large. Our approach is thus not designed to measure labor displacement but to identify areas of likely *augmentation*. This is consistent with evidence that automation technologies often reallocate rather than eliminate work, enabling workers to specialize in tasks that are less automatable and potentially more rewarding (Gong and Png, 2024). Moreover, as Dixon et al. (2021) show, robotics adoption can reorganize firms by increasing employment while reducing the relative share of managers.

Connection with forecasting technology effects. Methodologically, our work is related to research that forecasts the potential effects of other emerging technologies. Most closely, Felten et al. (2021) develop an index of occupational exposure to artificial intelligence (AI) using task-level data. As with AI, cobots are an emerging technology, and tools to evaluate their potential are still evolving (McElheran et al., 2022). The work of Jia et al. (2024) shows how artificial intelligence enhances productivity, and that the effects are greater for employees with greater skill. Other studies examine firm-level experiences with automation adoption, revealing challenges that can limit productivity gains if integration is poorly managed (Tong et al., 2021; Feigenbaum and Gross, 2024). As cobot adoption expands, similar empirical approaches can be used to measure realized impacts.

Finally, our focus on the *demographic* aspects of technology adoption adds another dimension. As Arntz et al. (2017) note, moving from technically feasible to *likely* adoption requires understanding where and for whom technology will be deployed. We build on this by documenting the demographic and geographic distribution of high-CAPI occupations, providing insight into which workers and communities are most likely to experience the first wave of cobot adoption. This complements evidence from MacCrory et al. (2014), who show that occupational skill composition shifted between 2006 and 2014, with growth in technology-complementary skills and decline in skills most directly substitutable by machines.

2. Cobot Capabilities and O*NET Occupational Tasks

To measure each occupation's potential for cobot adoption, our first objective is to understand both (1) the technical capabilities and limitations of cobots and (2) the tasks, activities, and work environments that define each occupation. The occupational data come from the Occupational Information Network (O*NET), sponsored by the U.S. Department of Labor and the Employment and Training Administration, which provides detailed task and work context information for 923 occupations.

2.1 Illustrations of Cobots in Occupations: Potential and Limitations

To illustrate both the promise and constraints of cobot integration, we highlight two occupational settings that differ markedly in their cobot compatibility.

High-Compatibility Example: Packaging and Food & Beverage. Packaging and palletizing tasks in the food and beverage industry provide a clear example of occupations with high cobot adoption potential. At Atria, a food manufacturer in Northern Europe, cobots (UR5 and UR10 models) were introduced to label, pack, and palletize products, replacing bulkier packaging equipment. Reported benefits included a payback period of roughly one year, dramatic reductions in changeover times (from about six hours to twenty minutes), and measurable increases in throughput and flexibility.[1] Similarly, Clearpack deployed a UR10 cobot for case erecting, packing, and palletizing in FMCG lines, emphasizing the compact footprint, safe collaborative design (requiring little or no safety guarding), and ease of redeployment across production lines. [2] These examples illustrate settings where tasks are repetitive, moderately physical, and highly structured, making them well-suited for cobot integration.

[1] See case study at apfoodonline.com.

[2] See case study at universal-robots.com.

Low-Compatibility Example: Automotive Assembly. Automotive final assembly provides a contrasting case, where cobot adoption potential is limited by payload requirements, task complexity, and safety constraints. Runola (2024) analyzes a human-centric automobile assembly line and finds that while certain subtasks—such as inspection, fastening, and moderate part handling—are technically feasible for cobots, many others remain challenging due to the need for large payload capacity, long reach, and high levels of dexterity and decision-making. [3] A feasibility analysis of cobots for tightening stations in automotive manufacturing similarly notes that weight limits and integration complexity constrain their usefulness. In these environments, conventional industrial robots or hybrid human-robot cells may remain more practical solutions.

Cobot potential is highest where tasks are repetitive, structured, and ergonomically demanding but fall within cobot payload and precision capabilities. Conversely, highly variable tasks requiring significant decision autonomy or heavy-object manipulation remain challenging, providing natural limits to CAPI scores for these occupations.

2.2 Identifying Relevant Tasks in O*NET

O*NET provides detailed occupational information for 923 occupations, including *abilities*, *skills*, *work activities*, and *work context*. We focus primarily on *work context*, which captures the "physical and social factors that influence the nature of work." This module provides rich information about task environment factors that are particularly relevant for cobot adoption, such as physical demands, repetitiveness, interpersonal requirements, and decision-making autonomy.[4] Table 1 lists the key O*NET measures we use to capture factors that enhance or limit cobot suitability.

Occupations vary widely in their composition of tasks and environments, so cobots may play very different roles depending on context. For example, cobots may be deployed in photography to execute precise, repeatable camera movements, or in warehousing and logistics for pick-and-place and stocking applications, where the environment can be engineered to facilitate automation. By contrast, cobots are less effective in occupations involving manipulation of extremely heavy objects, such as some automotive manufacturing tasks, where payload limitations reduce their usefulness.

Our index combines O*NET measures that either enhance or detract from cobot feasibility. We expect that occupations with significant physical demands—shown in the upper panel of Table 1—will generally have greater cobot potential. Repetitive motions also raise suitability for two reasons: (1) engineers can design and reuse solutions more easily, reducing implementation cost, and (2) repetitive motions are a major source of ergonomic risk for human workers (Armstrong et al., 1986; Bernard and Putz-Anderson, 1997), so automation offers a clear benefit. By contrast, occupations requiring high levels of interpersonal interaction or autonomous decision-making are less amenable to cobot collaboration, as unpredictable human factors reduce the effectiveness of automation. Finally, we include O*NET's "auto-degree" measure to rule out occupations that are

[3] See Runola (2024).

[4] While there are additional O*NET modules (e.g., *skills* and *work activities*), we find that much of the information is redundant. Including more modules does not materially improve precision in constructing the CAPI measure.

Table 1: Key O*NET Work Context Measures Determining Cobot Suitability

physical related measurements (+)	
(4.C.2.d.1.e)	Spend Time Kneeling, Crouching, Stooping, or Crawling
(4.C.2.d.1.g)	Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls
(4.C.2.d.1.h)	Spend Time Bending or Twisting the Body
repetitiveness (+)	
(4.C.2.d.1.i)	Spend Time Making Repetitive Motions
interpersonal skills (–)	
(4.C.1.a.2.c)	Public Speaking: How often do you have to perform public speaking in this job?
(4.C.1.a.4)	Contact With Others: How much does this job require the worker to be in contact with others in order to perform it?
(4.C.1.b.1.e)	Work With Work Group or Team: How important is it to work with others in a group or team in this job?
(4.C.1.b.1.f)	Deal With External Customers: How important is it to work with external customers or the public in this job?
(4.C.1.b.1.g)	Coordinate or Lead Others: How important is it to coordinate or lead others in accomplishing work activities in this job?
(4.C.1.c.1)	Responsible for Others' Health and Safety: How much responsibility is there for the health and safety of others in this job?
(4.C.1.c.2)	Responsibility for Outcomes and Results: How responsible is the worker for work outcomes and results of other workers?
(4.C.1.d.1)	Frequency of Conflict Situations: How often are there conflict situations the employee has to face in this job?
(4.C.1.d.2)	Deal With Unpleasant or Angry People: How frequently does the worker have to deal with unpleasant, $\cdots$ individuals $\cdots$?
(4.C.1.d.3)	Deal With Physically Aggressive People: How frequently does this job require the worker to deal with $cdots$?
decision making (–)	
(4.C.3.a.1)	Consequence of Error: How serious would the result usually be if the worker made a mistake that was not readily correctable?
(4.C.3.a.2.a)	Impact of Decisions on Co-workers or Company Results: What results do your decisions usually have on other people or $\cdots$?
(4.C.3.a.2.b)	Frequency of Decision Making: How frequently is the worker required to make decisions that affect other people, $\cdots$?
(4.C.3.a.4)	Freedom to Make Decisions: How much decision making freedom, without supervision, does the job offer?
physical proximity (–)	
(4.C.2.a.3)	Physical Proximity: To what extent $\cdots$ worker to perform job tasks in close physical proximity to other people?
autodegree (–)	
(4.C.3.b.2)	Degree of Automation: How automated is the job?

already highly automated (or conversely, those for which automation is extremely unlikely).

With the task-level measures in Table 1, we capture the main factors that enhance or limit cobot suitability, from physical demands and repetitiveness to interpersonal, decision-making, and automation characteristics. Combining these components yields the Cobot Adoption Potential Index (CAPI), which provides a consistent, occupation-level measure of where cobots could technically be deployed. In the next section, we apply CAPI to U.S. employment data to explore its geographic, demographic, and industry distribution and to assess where cobot adoption is likely to have the greatest potential impact.

3. Creating the Cobot Adoption Potential Index

In this section, we describe the construction of the Cobot Adoption Potential Index (CAPI). Using O*NET data, we first identify tasks within occupations that are potentially suitable for cobots, drawing on studies from the engineering and robotics design literature. We then construct several candidate indices of cobot adoption potential based on these tasks. To select a preferred index, we evaluate how well each candidate replicates expert assessments of occupations that have been previously categorized as having high or low cobot potential. The index that performs best becomes our CAPI measure, which we then apply to the full set of occupations to provide a consistent,

Table 2: Qualitative Assessment of Cobot Compatibility for Selected Occupations

SOC Code	Occupation Title	Compatibility
512011	Aircraft structure, surface, rigging and systems assemblers	high
536051	transportation inspectors	low
516041	Shoe and leather workers and repairers	low
512061	Timing device assemblers and adjusters	low
473011	Helpers—brickmasons, blockmasons, stonemasons, and tile and marble setters	high
172111	Health and Safety Engineers, Except Mining Safety Engineers and Inspectors	low
519071	Gem and diamond workers	low
514071	Foundry mold and coremakers	high
518091	Chemical plant and system operators	high
512021	Coil winders, tapers, and finishers	high
519192	Cleaning, washing, and metal pickling equipment operators and tenders	high
492091	Avionics technicians	low
513022	Meat, poultry, and fish cutters and trimmers	high
516011	Laundry and dry-cleaning workers	low
519111	Packaging and filling machine operators and tenders	high
537062	Recycling and reclamation workers	high

quantitative measure of cobot adoption potential. In the next section, we use this measure to examine demographic, geographic, and industry patterns.

3.1 Choosing the CAPI Index

To identify the most accurate index, we first construct several candidate measures of cobot adoption potential using combinations of O*NET variables. We then evaluate how well each candidate index classifies occupations as "high" or "low" cobot compatibility using a small validation sample from prior work.

3.1.1 Occupation Test Sample

We draw a subsample of occupations from Liu et al. (2022), who use O*NET task data and information about cobot capabilities to rate occupations by their collaborative utility. Occupations are classified as having "high" potential if they involve physical tasks that are well-structured and easily modeled (e.g., with defined workspace processes and feasible sensing requirements) and feature relatively few tasks requiring frequent judgment, inspection, or interpersonal connection. Table 2 lists the 16 occupations used for validation, nine of which are classified as high cobot compatibility and seven as low.

3.1.2 Index Selection

For each candidate index, we generate an indicator for cobot compatibility, which equals one when the index value for an occupation is above the p-th quantile of the index distribution and zero otherwise:

$$\mathbf{I}(\text{compatible with cobot})_o = \begin{cases} 1 & \text{if CAPI}_o \geq p\text{-th quantile} \\ 0 & \text{if CAPI}_o < p\text{-th quantile.} \end{cases} \quad (1)$$

We test multiple quantile thresholds (p) and calculate the precision rate for each candidate index relative to the expert-classified validation sample. Table 3 illustrates this procedure using a simple hypothetical ranking of occupations.

Table 3: Example of How Threshold is Selected

occ	1	2	3	4	5	6	7	8	9	10	
cobot potential	low									high	
true compatibility	0	0	0	0	0	0	1	1	1	1	
constructed index(e.g.)	0.5	1.3	4.6	5.1	6.2	6.8	10.5	12.2	14.2	16	
Pick a specific threshold.											
Compatible indicator = 1 If the index value ≥ threhold											
	indicator for compatible or not										precision rate
30th quantile	0	0	1	1	1	1	1	1	1	1	0.6
50th quantile	0	0	0	0	1	1	1	1	1	1	0.8
70th quantile	0	0	0	0	0	0	1	1	1	1	1
90th quantile	0	0	0	0	0	0	0	0	1	1	0.8

We then apply this procedure to our subsample across all candidate indices and quantile thresholds. Table A5 in Appendix A.2 reports the precision rates for the 70th quantile, while Table A1 shows results across thresholds. Among all candidates, *Index 5* at the 70th quantile achieves the highest precision rate (87.5%), and we adopt this combination as our preferred CAPI measure. **Composition of Index 5.** Our preferred measure, Index 5, combines several key dimensions of O*NET *work context* that theory and prior literature identify as relevant for cobot adoption. Specifically, it sums the standardized scores for physical task measures (kneeling, stooping, handling objects), adds weight for repetitiveness, and subtracts standardized scores for dimensions that reflect barriers to cobot use, including decision-making autonomy, interpersonal skill intensity, and physical proximity requirements. Finally, it incorporates O*NET's "degree of automation" to downweight occupations that are already highly automated. The resulting index is normalized to have a mean of 50 and a standard deviation of 10 across occupations, yielding a continuous measure from 0 to 100 that is comparable across the full set of 923 detailed occupations.

3.2 Categorizing Occupations

Having selected the preferred index, we apply it to the full set of 923 O*NET occupations. Each occupation receives a CAPI score, normalized to range from 0 to 100. Figure 1 shows the distribution of scores across occupations. For interpretability, we define occupations in the top 30% of the distribution as having "high" cobot adoption potential, where there is the most pronounced gap in scores. Occupations below this cutoff are classified as "low" potential.

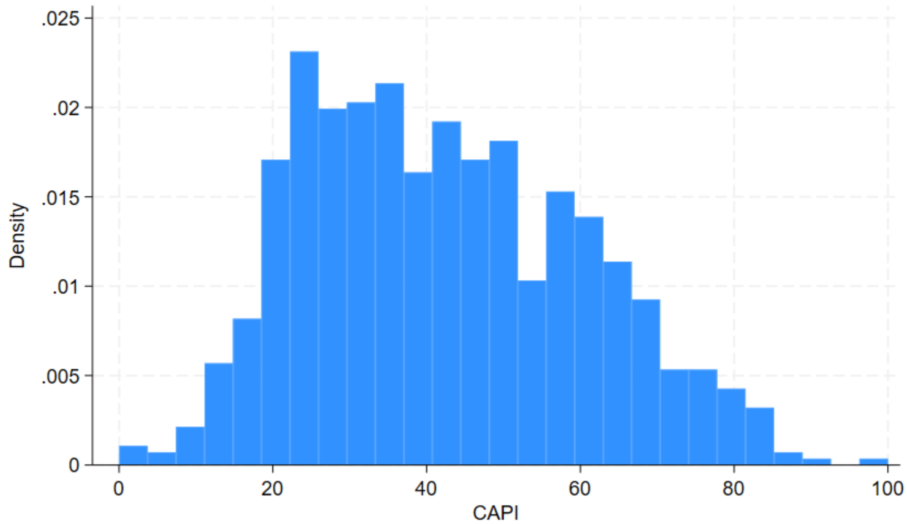


Figure 1: Distribution of CAPI Scores Assigned to Occupations

Table A6 (Appendix A.1) lists representative occupations by quartile. High-CAPI occupations include "Maids and Housekeeping Cleaners," "Meat, Poultry, and Fish Cutters and Trimmers," and "Stockers and Order Fillers," while low-CAPI occupations range from "Telecommunications Equipment Installers and Repairers" to occupations with very low scores such as "Judges, Magistrate Judges, and Magistrates" and "Family Medicine Physicians."
These categorizations provide a systematic picture of where cobot adoption is technically feasible and set the stage for the next section, where we link these scores to regional, demographic, and industry data to explore broader implications for the workforce and policy.

4. The Geography and Demography of High-Potential Occupations

Having estimated which occupations have the greatest potential for cobot integration, we now examine three dimensions of their distribution: (1) the geographic concentration of cobot-suitable occupations within the United States, (2) the demographic composition of workers currently in these occupations, and (3) the potential for cobots to improve workplace safety.

For these analyses, we link the Cobot Adoption Potential Index (CAPI) to additional data sources. We connect occupation-level CAPI scores to the American Community Survey (ACS) microdata (IPUMS ACS, 2015-2019) to summarize worker age, income, education, and other characteristics by CAPI group. We also merge CAPI with occupation-level injury incidence data from the Bureau of Labor Statistics Injuries, Illnesses, and Fatalities (IIF) program (Bureau of Labor Statistics, U.S. Department of Labor, 2020) to assess whether high-CAPI occupations face elevated risks that cobots could mitigate.

4.1 Geography of Cobot Potential

We begin by examining which regions have the highest concentration of workers in cobot-compatible occupations. Understanding the geography of cobot potential is valuable for managers and policymakers seeking to anticipate where competitive dynamics and workforce needs may shift most rapidly. We construct occupation-weighted CAPI averages at both the state and Metropolitan Statistical Area (MSA) levels using the May 2019 Occupational Employment and Wage Statistics (OEWS) data from Bureau of Labor Statistics, U.S. Department of Labor (2019).

State- and MSA-level distributions. Figure 2 shows the distribution of average CAPI scores across states, while Figure 3 presents weighted averages for selected MSAs.[5] Dark blue shading represents regions with lower average cobot adoption potential, whereas red shading represents regions with higher potential. These maps indicate that cobot adoption potential is not simply a function of population density; for example, Chicago's MSA has a lower average CAPI than Fresno's, despite employing a much larger number of workers overall.[6]

Occupations in high CAPI MSAs and states. Table A7 lists the ten MSAs with the highest cobot adoption potential and, for the top 5 MSAs, the largest occupations within the MSA based on total current employment level and rate per 1,000 jobs. These are all MSA with highly specialized local economies, with the top three (Madera, Salinas, and Visalia-Porterville, California) being agricultural. The MSA with the fourth highest CAPI is Kahului-Wailuku-Lahaina, Hawaii, specializing in tourism, with the fifth highest, Dalton, Georgia, specializing in carpet manufacturing.

[Insert Figure A7 here.]

Table A8 lists the top 10 States which are with the highest cobot adoption potential (shown also in Figure 2) along with, for the five states with the highest average CAPI, the largest occupations by employment. Not too surprisingly, there is less variation across states in the largest occupations compared to the variation across smaller and more specialized MSAs. However, the top two states, Nevada and Hawaii, host a large tourism industry, while Wyoming, Indiana, and South Dakota follow, with relatively higher shares of agricultural, manufacturing, and resource-intensive occupations. While there is often a focus on collaborative robots in industrial and manufacturing settings, this supports the large potential for adoption in the service and hospitality sectors studied by Decker et al. (2017).

[Insert Table A8 here.]

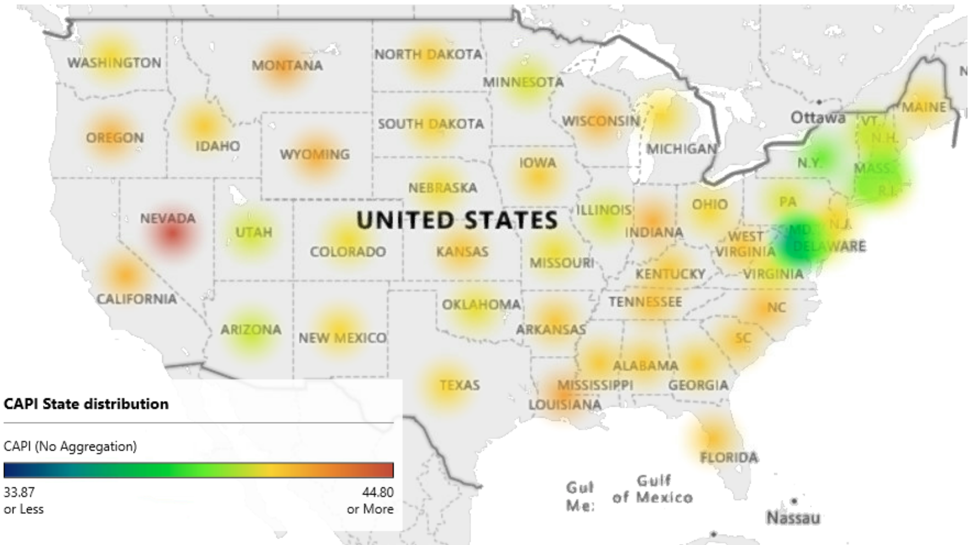
4.2 Worker Characteristics and Cobot Compatibility

Next, we examine the demographic characteristics of workers currently employed in high- versus low-CAPI occupations. This helps forecast who is most likely to be affected by cobot adoption and

[5] A full map of all MSAs is shown in Figure A6.

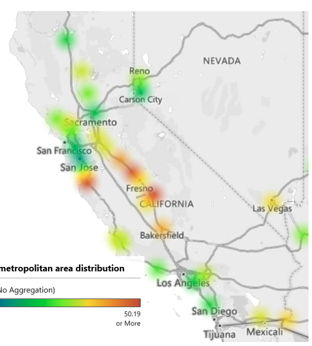
[6] An alternative figure based on absolute numbers would primarily reflect population size rather than intensity of potential adoption.

Figure 2: CAPI distribution at State level

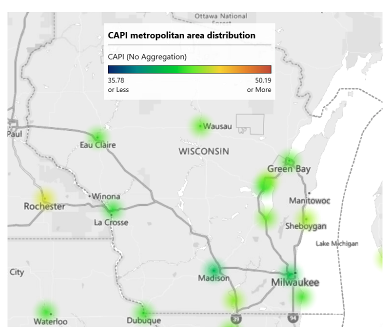


Data Source: O*NET is used to construct the Cobot Adoption Potential Index (CAPI). Occupational employment information by metropolitan statistical area and by state comes from the May 2019 Occupational Employment and Wage Statistics (OEWS) by U.S. Bureau of Labor Statistics (BLS).

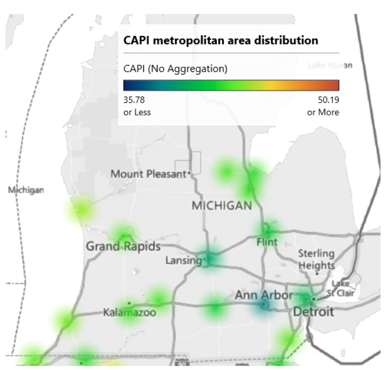
Figure 3: CAPI Distribution at Metropolitan Statistical Area Level, Detailed Examples



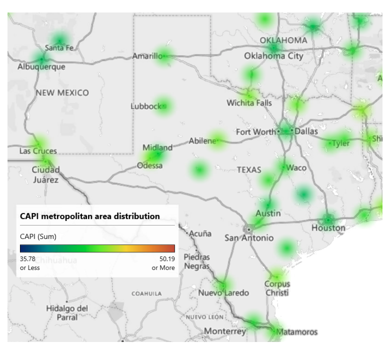
(a) California



(b) Wisconsin



(c) Michigan



(d) Texas

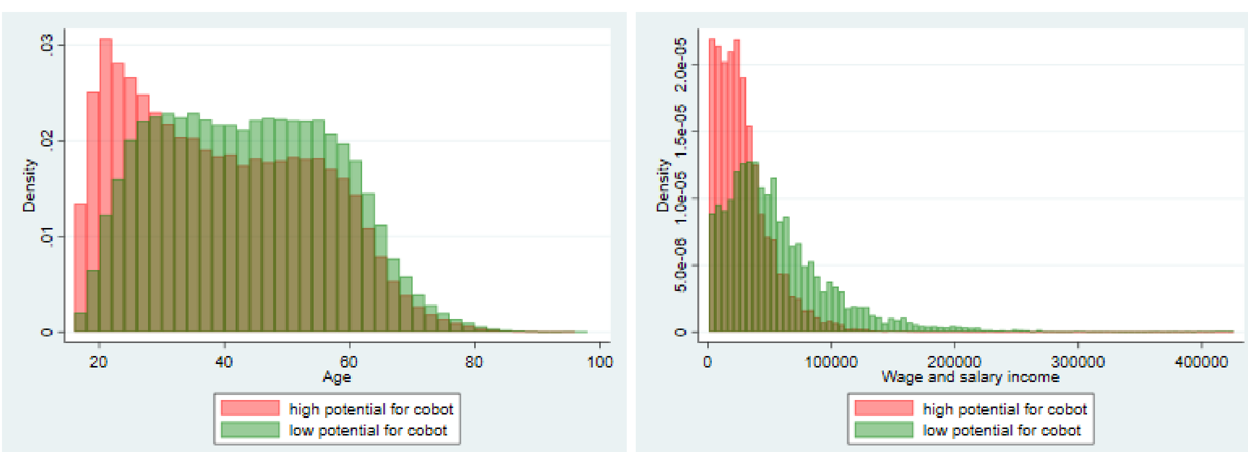
informs the design of policies such as training programs and educational investments.

We link CAPI scores to ACS microdata, using individual-level weights to obtain nationally representative results. Figure 4 shows the distributions of age (panel a) and income (panel b) for workers in occupations with high versus low CAPI scores. High-CAPI occupations tend to be younger on average, suggesting a workforce more likely to invest in human capital and adapt to new technology. However, these occupations also pay lower average annual wages, which may affect the financial feasibility of retraining efforts.

For this exercise, we use the American Community Survey (ACS) to connect the CAPI with worker demographic information. The ACS data is a nationally representative individual level dataset which is released annually and includes information about jobs and occupations, demographic characteristics, social characteristics like disability status and educational attainment, and economic characteristics like income. The rich information provided by the ACS data together with the constructed CAPI score allow us to analyze and understand the characteristics of people who are currently working in occupations with high cobot potential and with low cobot potential.

First, we consider the age distribution of workers in high- and low-cobot potential occupations. Figure 4, panel (a) shows the age distributions for those who are in occupations with a CAPI that indicates high or low potential of cobot adoption.[7] Among those in occupations with high CAPIs, the age distribution shows much younger average and modal ages (in red) compared to those in occupations with low CAPIs (in green). A young workforce is promising for the ability and willingness of workers to adapt to new technology, since investment in human capital is more intense for an individual with more potential working years ahead. We also consider the income level of workers in these occupations. The graph in panel (b) shows, more strikingly, that the total annual income among those in high-cobot potential jobs have lower annual income on average. Income levels may be of interest when considering the financial trade-offs of adopting cobots.

Figure 4: Distribution by Income and Age Groups



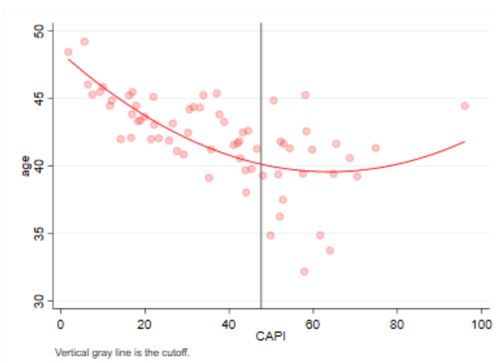
(a) age (b) income

[7]ACS individual-level personal weights are used in the summary table and all the following graphs.

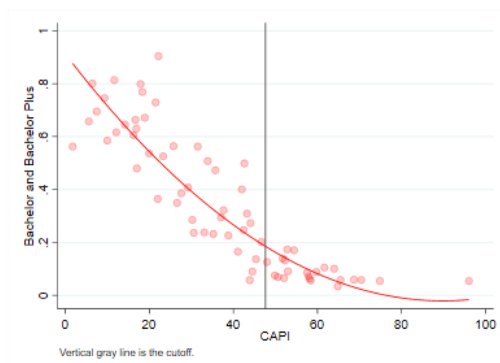
Next, we analyze demographic factors using the full range of CAPI scores instead of a binary measure. In the set of graphs in Figure 6, each point represents, for all occupations with a given small range of CAPI score around that point, the average level of the variable being measured. In panel (a), we see the average age of workers in occupation by CAPI score, where for occupations with CAPI scores that would be considered high, the average age is more dispersed and the trend is flatter. For occupations with low CAPI scores, the average age is not only higher overall, but also shows a less dispersed pattern with a clear trend downward as CAPI scores increase. Still, the lower overall age for occupations with higher CAPI scores suggests that workers will be at a stage of their careers where they can easily adjust their skills and adapt to new technologies.

Another way of analyzing the adaptability to workers is by education level. Figure 6 (b) reports the average share of workers with at least a bachelor degree. The graph shows a more striking trend than age, with workers in high cobot potential occupations having lower education on average. In terms of implications, a workforce with lower education may need more investment in training to utilize cobots, particularly if the cobots require computer programming to adapt them to new environments.

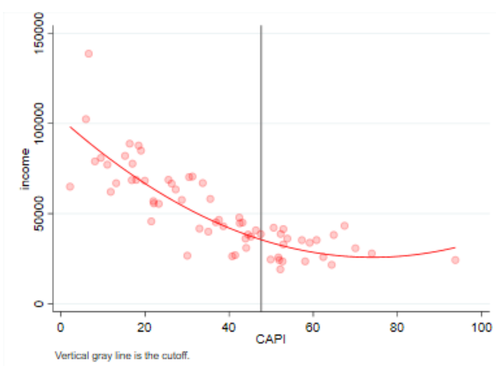
Figure 5: Relationships Between Demographics and Occupation CAPI Scores



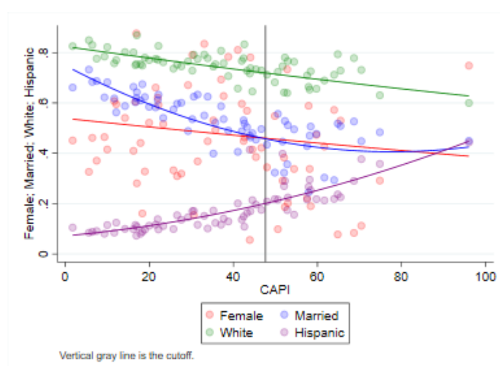
(a) age



(b) education (proportion of workers with bachelor and bachelor+ degree)



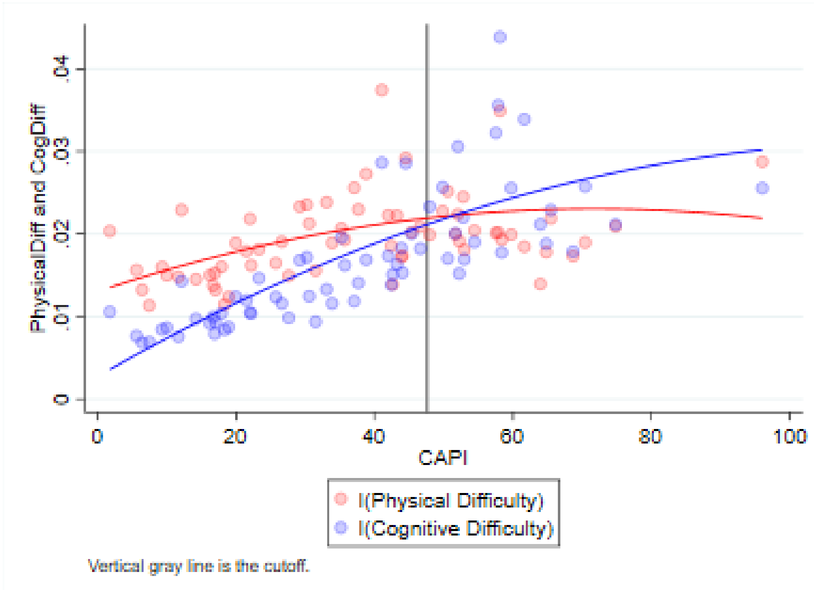
(c) income



(d) other demographic indicators

Finally, we highlight a few other demographic characteristics that we can observe from the ACS

Figure 6: Relationships Between Cognitive and Physical Difficulty and Occupation CAPI Scores



data. Graph (c) plots the patters for average income. As we saw with the binary measure, workers in higher CAPI occupations also tend to receive lower wages. Graph (d) of Figure 6 shows the patterns for other demographic variables on percent married, percent female, and race. Occupations with CAPI scores that predict high potential for cobot adoption are made up of workers who are more likely to be Hispanic and less likely to be married.

4.3 Physical Assistance, Injury Rates, and Cobots

Finally, we use our index to analyze the potential for cobots to improve the physical work environment. Cobots have the potential to make physical tasks more ergonomic and safe for workers.[8] In this application, we focus on they types of workplace barriers workers might face as well as injury rates in the occupations with the highest potential for cobots.

These findings suggest cobots could expand opportunities for older workers and those with disabilities through a wider range of occupations they are able to perform. Reduction of potential injury rates very attractive to both prospective workers and firms. Using the ACS data, Figure 6 shows that workers in occupations with higher CAPI scores are more likely to have cognitive difficulties and somewhat more likely to have physical difficulties. Cobots have the capacity to ameliorate some of these physical difficulties.

Next we connect occupation CAPI scores to data on injury and exertion by occupation with the Injuries, Illnesses, and Fatalities (IIF) 2020 data from the Bureau of Labor Statistics (BLS). The

[8]For instance, using data from the US and Germany, Gihleb et al. (2022) find that the introduction of robots reduced the physical intensity and injury rates of workers exposed to industrial robots in their workplaces.

adoption of cobots has the potential to reduce net injury and strain. As we show, occupations with high CAPI scores—being more physically involved—have on average higher total injury incidence rates. Cobots have the potential to improve workplace safety and reduce the rate of workplace injury. All the following analyses use the injury incidence rate as the measurement for injury-related questions.

The relationship between occupational CAPI scores and various incidence rates per 10,000 workers is shown in the graphs in Figure 7 and in Table A3. Looking first at Figure 7, we see that in the top green trend lines in panels (a) and (b), the total injury and total average overexertion rates increase as CAPI score increases. In these same graphs, sub-categories show a similar, though muted, pattern. In panel (c), we see a weak relationship between CAPI and injury through exposure to harmful substances or environments in the blue trend line, with a positive relationship between CAPI scores and injury by contact with objects or equipment. Finally, panel (d) shows a weak relationship between inpatient hospitalization and CAPI scores (in red), but strong relationships between emergency room visits and CAPI scores, as well as total treatments at medical facilities and CAPIs.

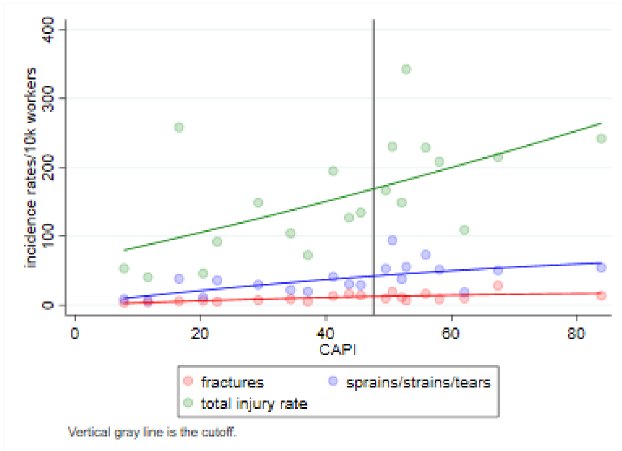
Table A3 tabulates the summary for the same data where occupations are grouped as having either high or low cobot adoption potential. Here too we can see that occupations with high cobot adoption potential have significantly higher rates of injury, with the total injury incidence rate per 10,000 workers being 102.8 for workers in occupations with low CAPI scores and 188.7 for workers in occupations with high CAPI scores. In all injury-related aspects, as well as medical treatment facility visits, the average incidence rate is significantly higher for occupations with high cobot potential. This is relevant because, on net, cobots have the potential to reduce injuries if integrated strategically, which is highly valuable for all parties.

Cobot adoption potential is widely distributed across the United States but is particularly concentrated in agricultural, manufacturing, and service-oriented regions with specialized local economies. Workers in high-CAPI occupations are younger on average but earn lower wages and have lower educational attainment, suggesting that targeted training and workforce development programs may be needed to realize the productivity and safety benefits of cobots. Finally, the significantly higher injury rates observed in high-CAPI occupations point to the potential for cobots to improve job quality and workplace safety if deployed thoughtfully. These findings highlight opportunities for policymakers and managers to direct training, safety initiatives, and technology investment to the workers and communities most likely to be affected.

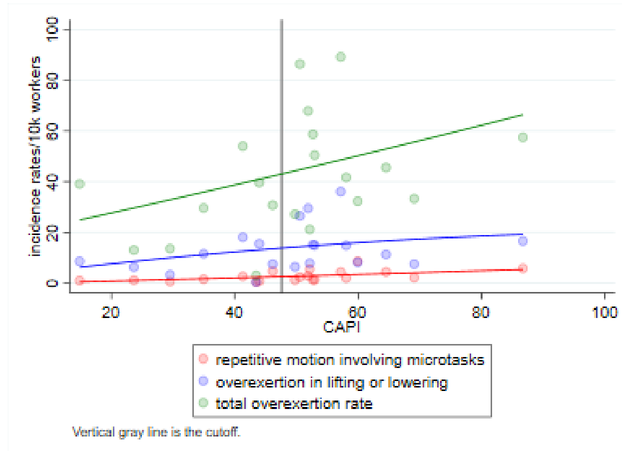
5. Discussion and Conclusion

Collaborative robots are an expanding technology designed to work alongside human workers, with the potential to augment human tasks, improve workplace safety, and increase productivity. While cobots may lead to some automation and displacement in certain tasks, their defining feature is their ability to complement rather than fully replace human labor. In this paper, we introduced

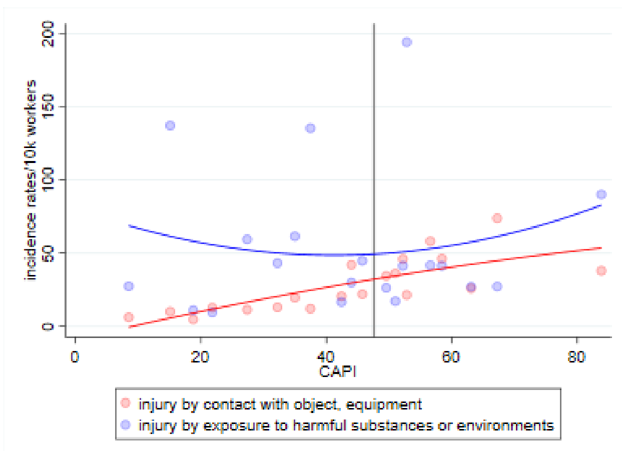
Figure 7: Relationship Between Injury Rates and Occupation CAPI



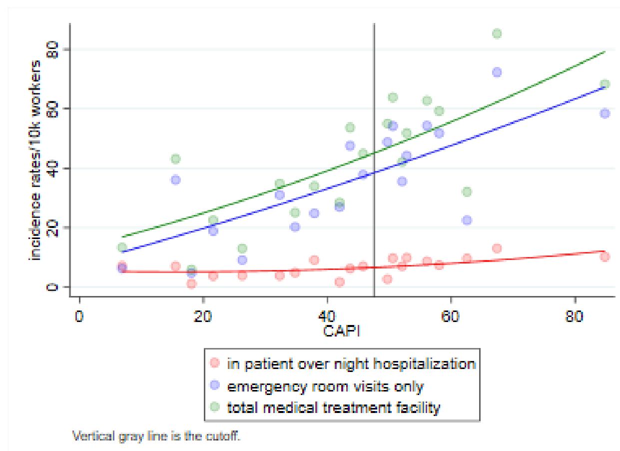
(a) total injury rate



(b) total overexertion rate



(c) other injury



(d) total medical treatment

the Cobot Adoption Potential Index (CAPI), a simple, occupation-level measure based on detailed task characteristics from O*NET.

We demonstrated how CAPI can be applied to three key domains: (1) the geography of cobot potential, highlighting regions where adoption is most feasible and competitive pressures are likely to drive investment; (2) the demographic profile of workers in high-CAPI occupations, which helps anticipate how readily the workforce can adapt and which groups may need targeted training support; and (3) the relationship between CAPI and occupational injury rates, underscoring the potential for cobots to make physically demanding jobs safer and more attractive.

Policy and Managerial Implications. Our results suggest several actionable takeaways for policymakers and managers. First, high-CAPI occupations are concentrated in particular MSAs and states—often in agriculture, hospitality, and certain types of manufacturing—providing a roadmap for where workforce development resources could be prioritized. Second, the relatively low educational attainment of workers in high-CAPI occupations implies that training programs should focus on practical, job-embedded skill development rather than lengthy formal retraining. Third, the elevated injury rates we document highlight an important opportunity: cobots could reduce workers' physical strain, potentially extending careers and reducing employer costs from injury-related absences. Together, these findings suggest that well-designed policies and investments can maximize the benefits of cobot technology while minimizing risks of displacement.

Limitations and Future Research. While our approach highlights where cobots *could* be adopted, it does not fully address whether they *will* be adopted. In particular, information on the relative costs of cobots versus local labor, as well as firm-specific return-on-investment calculations, are critical to determining adoption decisions. CAPI should therefore be viewed as an upper bound on eventual adoption rates, conditional on current technology. Moreover, cobot capabilities are rapidly evolving, which means that future updates to CAPI could reveal new opportunities for integration.

Cobots represent a distinctive blend of automation and collaboration, allowing firms to redesign workflows in ways that complement human labor rather than merely replace it. By providing a transparent, data-driven measure of cobot adoption potential, the CAPI offers a tool for researchers, managers, and policymakers seeking to understand where cobots can create the most value. As adoption accelerates, future work should track realized impacts on employment, productivity, and job quality, ensuring that the promise of cobots translates into tangible benefits for workers, firms, and society.

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A.1 Additional Tables and Figures

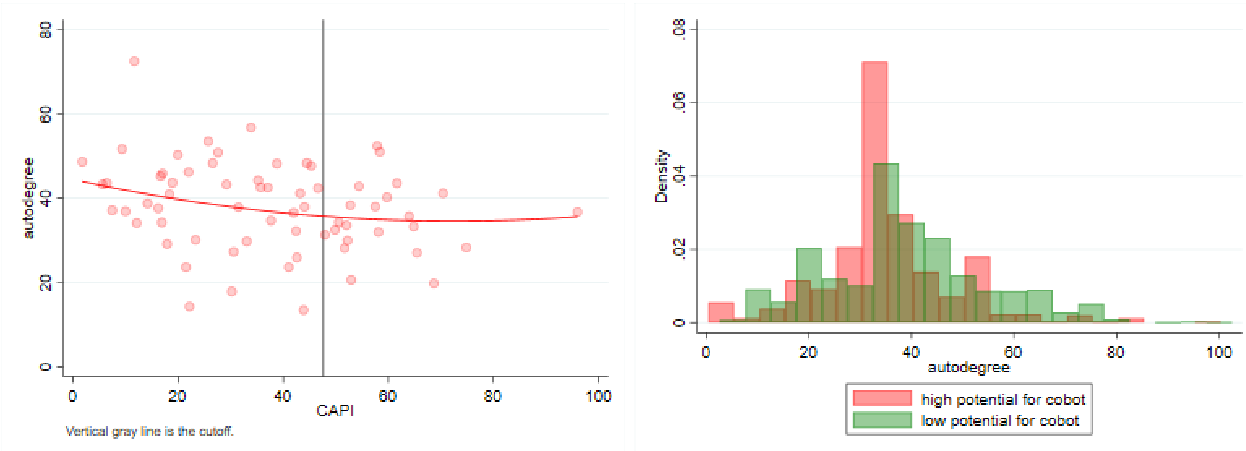
Table A1: Precision Rates of Candidate Indices Across Thresholds, Sums

			precision rate | threshold=x^{th} quantile											
version	data source	⋯	60^{th}	62^{th}	64^{th}	66^{th}	68^{th}	70^{th}	72^{th}	74^{th}	76^{th}	78^{th}	80^{th}	⋯
1	work context		0.750	0.813	0.813	0.813	0.813	0.813	0.813	0.750	0.688	0.688	0.688	
2	work context		0.750	0.688	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.750	
3	work context		0.625	0.625	0.688	0.625	0.688	0.688	0.688	0.625	0.563	0.625	0.500	
4	work context		0.563	0.563	0.563	0.563	0.688	0.688	0.625	0.625	0.688	0.625	0.563	
5	work context		0.750	0.813	0.813	0.813	0.813	0.875	0.813	0.688	0.625	0.500	0.500	
6	work context		0.625	0.625	0.688	0.625	0.563	0.625	0.625	0.688	0.625	0.563	0.500	
7	work context		0.750	0.750	0.813	0.813	0.813	0.750	0.750	0.750	0.688	0.688	0.500	
8	work context		0.750	0.750	0.750	0.813	0.750	0.750	0.750	0.688	0.688	0.688	0.563	
9	work context		0.688	0.688	0.688	0.750	0.750	0.688	0.688	0.688	0.625	0.625	0.500	
10	work context		0.750	0.813	0.750	0.813	0.813	0.813	0.813	0.750	0.750	0.625	0.563	
11	work context		0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	0.688	
12	work context		0.625	0.625	0.688	0.688	0.688	0.750	0.750	0.750	0.688	0.688	0.750	
13	work context		0.625	0.625	0.688	0.688	0.750	0.750	0.750	0.750	0.813	0.813	0.688	
14	work context		0.688	0.750	0.750	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	
15	work activities		0.688	0.688	0.625	0.563	0.563	0.563	0.563	0.563	0.500	0.500	0.500	
16	work activities		0.688	0.688	0.688	0.688	0.688	0.625	0.625	0.563	0.625	0.563	0.625	

Table A2: Precision Rates of Candidate Indices Across Thresholds, Means

			precision rate | threshold=x^{th} quantile											
version	data source	⋯	60^{th}	62^{th}	64^{th}	66^{th}	68^{th}	70^{th}	72^{th}	74^{th}	76^{th}	78^{th}	80^{th}	⋯
1	work context		0.750	0.813	0.813	0.813	0.813	0.813	0.813	0.750	0.688	0.688	0.688	
2	work context		0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.813	0.750	0.750	
3	work context		0.688	0.688	0.688	0.688	0.625	0.625	0.625	0.688	0.625	0.688	0.750	
4	work context		0.625	0.625	0.625	0.625	0.563	0.563	0.563	0.563	0.563	0.688	0.688	
5	work context		0.688	0.688	0.688	0.688	0.750	0.813	0.813	0.813	0.813	0.813	0.875	
6	work context		0.625	0.625	0.625	0.625	0.625	0.625	0.625	0.688	0.625	0.563	0.625	
7	work context		0.688	0.688	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.750	
8	work context		0.688	0.688	0.688	0.750	0.750	0.750	0.750	0.813	0.813	0.750	0.750	
9	work context		0.625	0.625	0.625	0.688	0.688	0.688	0.688	0.750	0.750	0.688	0.688	
10	work context		0.750	0.750	0.750	0.750	0.750	0.813	0.750	0.750	0.813	0.813	0.813	
11	work context		0.688	0.688	0.688	0.688	0.688	0.750	0.688	0.688	0.688	0.688	0.688	
12	work context		0.688	0.688	0.688	0.750	0.750	0.750	0.688	0.688	0.688	0.750	0.688	
13	work context		0.688	0.688	0.750	0.750	0.750	0.750	0.750	0.813	0.750	0.688	0.625	
14	work context		0.750	0.750	0.750	0.750	0.750	0.750	0.813	0.813	0.813	0.813	0.813	
15	work activities		0.625	0.563	0.563	0.563	0.563	0.563	0.500	0.500	0.500	0.500	0.500	
16	work activities		0.688	0.688	0.625	0.625	0.625	0.563	0.625	0.625	0.563	0.563	0.500	

Figure A2: Correlation Between CAPI and Automation Degree



(a) auto degree

(b) auto degree by cobot compatible group

A.2 Alternative Indices and Selection

We constructed several potential indices as a function of the O*NET work context categories. We used both linear and non-linear combinations of the context measures. To begin, we first standardized each of the work context measurements with mean zero and standard deviation of one. This was to eliminate the concern that the range of different measurements can be different, and to make preparations for constructing *cobot indices*.[9] We discuss five versions in detail below. Table A4 of the Appendix describes all the other versions that have been considered.[10] In the next section, we will discuss how we choose our preferred index from among these different options.

Index 1. The first candidate index version uses *physical related measurements* and *repetitiveness*. And for a given occupation o, the index is calculated in the following way. Conditional on repetitiveness being the same, the more physical related tasks included in the occupation, the higher the score. However, if very few of the tasks are repetitive, it will be hard to set up the function and use the cobot to assist which will lead to a low CAPI. This is true no matter how high the *physical measurements* are.

$$index1_o = \sum_{j \in \text{physical measurements}} j_o \times \text{repetitiveness}_o \tag{2}$$

In the equation, for the first term we use the sum of all physical measurements instead of using the mean. This is because we think that the "number" of tasks that are physically related are also vital in determining cobot compatibility and could have significance.

Index 2. Instead of using the product form, the second version uses the sum of *physical related measurements* and

[9]We do not re-weight each measurement based on the occupational labor supply. Since whether an occupation has the potential to be compatible with cobot should depend on the occupational technology attributes but not on how many workers are working in that occupation. From this perspective of view, it is not necessary to put more weights on occupations with larger size when constructing CAPI.

[10]Whenever it is in product form, we adjust so that product of two negative terms does not achieve the same outcome as the product of two positive terms. For visual clarity, it is not explicitly written out in the equation.

Table A3: Summary Statistics in Occupations Based on CAPI Group

	Compatibility with Cobot		
	Low potential	High potential	All
Demographics			
age	43.2	38.8	41.9
annual wage and salary income($)	58,544	29,703	49,576
female	0.50	0.43	0.48
married	0.57	0.41	0.52
white	0.76	0.69	0.74
Hispanic	0.14	0.25	0.17
high school degree	0.96	0.84	0.92
some collage	0.70	0.36	0.59
bachelor plus	0.45	0.10	0.34
ambulatory difficulty	0.02	0.02	0.02
cognitive difficulties	0.01	0.03	0.02
Injury related aspects*			
total injury rate	102.8	188.7	132.2
sprains/strains/tears	28.1	45.3	34.7
fractures	9.1	12.7	10.5
total injury rate for overexertion and body reaction	23.5	45.8	31.8
overexertion in lifting or lower	10.2	14.5	12.1
repetitive motion involving microtasks	1.6	3.6	2.5
other affiliated injuries			
contact with object, equipment	17.1	42.4	27.6
exposure to harmful substances or environments	45.1	60.3	50.4
Medical treatment facility visits**			
total medical treatment facility	27.7	52.5	36.6
emergency room visits only	24.6	45.2	32.2
inpatient/overnight hospitalization	5.5	8.3	6.6

* Incidence rates of nonfatal occupational injuries and illnesses involving days away from work by occupation and medical treatment facility visits, all U.S., private industry, 2020. *Source: Bureau of Labor Statistics*

** Incidence rates for nonfatal occupational injuries and illnesses involving days away from work per 10,000 full-time workers by occupation and selected nature of injury or illness, private industry, 2020. *Source: Bureau of Labor Statistics*

repetitiveness. Thus, this method separately considers the physicality of the task and how repetitive the tasks are.

$$index2_o = \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o \tag{3}$$

Index 3. This version extends **Index 2** by including the need for interpersonal skills as an attenuating factor.

$$index3_o = \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o - \sum_{j \in \text{interpersonal skills}} j_o \tag{4}$$

Index 4. This version brings *physical proximity* and *auto-degree* into consideration. Conditional on everything else being the same, if the job requires the worker to perform tasks in a very close physical proximity to other people, it will be hard to set up the cobot under this situation. In the O*NET data, the higher the *physical proximity*, the closer the distance. Therefore, *physical proximity* is negatively correlated with cobot collaboration potential. *Auto-influence* is created based on the auto-degree. If the auto-degree of a certain occupation is too high or too low relative to the median auto-degree of all the occupations, the value of *auto-influence* will be very negative and decrease the CAPI. When auto-degree is too high, it might have already been automated and have no room for cobot collaboration. When the auto-degree is too low, it may be extremely hard to assign any of the tasks to robot or cobot.

$$\begin{aligned} \text{auto-influence}_o &= -\left[\text{auto-degree}_o - \text{median(auto-degree)}\right]^2 \\ index4_o &= \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o \\ &\quad - \sum_{j \in \text{interpersonal skills}} j_o - \text{physical proximity}_o + \text{auto-influence}_o \end{aligned} \tag{5}$$

Index 5. In the fifth version, we substitute the *interpersonal skills* of **Index 3** with *decision making* as an alternative attenuating factor. If an occupation requires the worker to frequently make decisions that have impacts on other people, if the consequence of each decision is serious, or if any errors can lead to a severe outcome, then this occupation may not be a good candidate and be with low CAPI.

$$index5_o = \sum_{j \in \text{physical measurements}} j_o + \text{repetitiveness}_o - \sum_{j \in \text{decision making}} j_o \tag{6}$$

In addition to using the sum of the measurements as the measure for each dimension, we considered other versions such as simple averages or using the principle component analysis to reduce the dimension and to construct the components which can expressing the maximum information from the original measurements to improve the quality of the information.

Principle Component Analysis. Using the Kaiser-Guttman criterion, we only keep those components whose eigenvalues are above 1.0 and believe that these components can capture considerable amount of information in the data. Take the *interpersonal skill* dimension for example. Under this dimension there are ten measurements and principal component analysis reveals that only the first three components are with eigenvalues greater than 1.0. By the rule of thumb, we only keep those three components and therefore the dimension for interpersonal skill measurements decreases from ten to three. Inside Table A4, PCA(physical measurements) is then calculated in the following way:

$$\text{PCA(physical measurements)} = \textit{component } 1 + \textit{component } 2 + \textit{component } 3. \tag{7}$$

The same logic applies to other principle component analysis listed in the table.

Using means instead sums to construct the CAPI. Comparing with all the '*sum*' versions listed in Table A4, the '*mean*' versions' precision rates are no higher than 87.5%. It is found that *Index5* consistently provides the best results, though the threshold is at the 80th quantile under this '*mean*' version. For worries that if the threshold of dividing the whole population into high and low cobot potential group is too high(or too low), we may have fewer information for the high potential group(or low potential group). We have preference for the threshold to be somewhere near the middle. Therefore, we keep using '*sum*' version with *Index5* and 70th quantile as the threshold to construct our CAPI in later analysis.

Table A4: Alternative CAPI Indices

version	data source	description
1	work context	$\sum$ physical measurements $\times$ repetitiveness
2	work context	$\sum$ physical measurements + repetitiveness
3	work context	$\sum$ physical measurements + repetitiveness - $\sum$ interpersonal skill measurements
4	work context	$\sum$ physical measurements + repetitiveness - $\sum$ interpersonal skill measurements - physical proximity + auto-influence)
5	work context	$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom
6	work context	$\sum$ physical measurements + repetitiveness - $\sum$ interpersonal skills - $\sum$ decision making freedom
7	work context	$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom - physical proximity
8	work context	$\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom + auto-influence
9	work context	$[\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom$]$ $\times$ $\sum$ interpersonal skills
10	work context	$[\sum$ physical measurements + repetitiveness - $\sum$ decision making freedom$]$ $\times$ auto-influence
11	work context	PCA(physical measurements) + repetitiveness - PCA(interpersonal skills) - PCA(decision making freedom) - physical proximity + auto-influence
12	work context	PCA (physical measurements) + repetitiveness - PCA(interpersonal skills) - PCA(decision making freedom)
13	work context	PCA(physical measurements) + repetitiveness - PCA(interpersonal skills)
14	work context	PCA(physical measurements) + repetitiveness - PCA(decision making freedom)
15	work activities	$\sum$ physical measurements - $\sum$ Interaction with people - $\sum$ decision making
16	work activities	PCA(physical measurements) - PCA(Interaction with people) - PCA(decision making)

Notes: PCA standards for principle component analysis. Other versions using mean instead of sum have also been tested, while the precision rate is no higher than 87.5%. The results for the '*mean*' version is listed in the Table A2 in the Appendix.

T. Tables and Figures

Table A5: Precision Rate of all Indices with Threshold at 70th Quantile

index version	data source	precision rate	assessments matched
1	work context	0.813	13 out of 16
2	work context	0.750	12 out of 16
3	work context	0.688	11 out of 16
4	work context	0.688	11 out of 16
5	work context	0.875	14 out of 16
6	work context	0.625	10 out of 16
7	work context	0.750	12 out of 16
8	work context	0.813	13 out of 16
9	work context	0.688	11 out of 16
10	work context	0.813	13 out of 16
11	work context	0.688	11 out of 16
12	work context	0.750	12 out of 16
13	work context	0.750	12 out of 16
14	work context	0.750	12 out of 16
15	work activities	0.563	9 out of 16
16	work activities	0.625	10 out of 16

Figure A6: The Distribution of MSA-level CAPI Scores

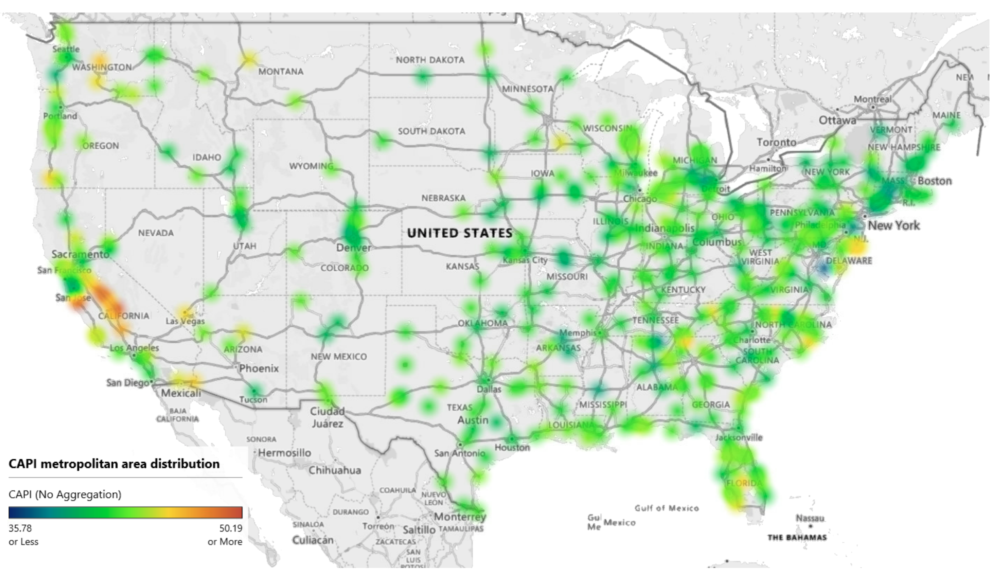


Table A6: Examples of Occupations in Different CAPI Quartile

Occupation Title*	CAPI Quartile	CAPI	Compatible with Cobot
Maids and Housekeeping Cleaners	4	100.00	high
Fiberglass Laminators and Fabricators	4	92.29	high
Textile Knitting and Weaving Machine Setters, Operators, and Tenders	4	88.04	high
Shoe Machine Operators and Tenders	4	87.52	high
Tile and Stone Setters	4	83.87	high
Floor Sanders and Finishers	4	83.67	high
Painters, Construction and Maintenance	4	83.34	high
Terrazzo Workers and Finishers	4	82.90	high
Cement Masons and Concrete Finishers	4	82.75	high
Pressers, Textile, Garment, and Related Materials	4	81.92	high
...			
Carpenters	3	55.95	high
Word Processors and Typists	3	55.92	high
Photographers	3	55.91	high
Earth Drillers, Except Oil and Gas	3	55.71	high
Stockers and Order Fillers	3	55.63	high
...			
Telecommunications Equipment Installers and Repairers, Except Line Installers	3	51.66	low
Animal Caretakers	3	51.58	low
Proofreaders and Copy Markers	3	51.23	low
Dental Laboratory Technicians	3	51.14	low
Food Service Managers	3	51.05	low
...			
Telemarketers	2	40.61	low
Counter and Rental Clerks	2	40.49	low
Insurance Appraisers, Auto Damage	2	40.45	low
Exercise Physiologists	2	40.39	low
Automotive Engineering Technicians	2	40.39	low
Aerospace Engineering and Operations Technologists and Technicians	2	40.39	low
Environmental Engineering Technologists and Technicians	2	40.38	low
Extruding and Drawing Machine Setters, Operators, and Tenders, Metal and Plastic	2	40.35	low
Retail Salespersons	2	40.31	low
Museum Technicians and Conservators	2	40.27	low
...			
Instructional Coordinators	1	27.82	low
Concierges	1	27.69	low
Materials Scientists	1	27.58	low
Interior Designers	1	27.47	low
Atmospheric and Space Scientists	1	27.40	low
...			
Real Estate Brokers	1	4.91	low
Judges, Magistrate Judges, and Magistrates	1	4.00	low
Psychiatrists	1	1.32	low
Neurologists	1	0.37	low
Family Medicine Physicians	1	0.00	low

* Occupations are listed based on the descending order of CAPI. Contains a subset of the 892 occupations, specifically those at the top of each quartile by CAPI, and at the top of the occupations categorized as having “low” cobot adoption potential.

Table A7: The Top Ten Metropolitan Areas with Highest CAPI

CAPI Rank	Metropolitan Statistical Area	High Potential Occupations	CAPI	Total Employment	The Number of Jobs in the Given Occupation per 1,000 Jobs in the Given Area
1	Madera, CA	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	81.48	6,340	135.8
		Cashiers	54.65	1,200	25.7
		Fast Food and Counter Workers	65.15	1,110	23.9
		Packers and Packagers, Hand	67.57	1,010	21.6
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	980	21.0
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	820	17.5
		Maintenance and Repair Workers, General	60.60	490	10.5
		...			
2	Salinas, CA	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	81.48	30,880	168.8
		Cashiers	54.65	4,900	26.8
		Fast Food and Counter Workers	65.15	4,390	24.0
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	4,200	22.9
		Waiters and Waitresses	67.21	3,990	21.8
		Maintenance and Repair Workers, General	60.60	2,130	11.6
		Maids and Housekeeping Cleaners	100.00	2,070	11.3
		...			
3	Visalia-Porterville, CA	Farmworkers and Laborers, Crop, Nursery, and Greenhouse	81.48	24,650	158.3
		Cashiers	54.65	4,820	31.0
		Fast Food and Counter Workers	65.15	3,680	23.6
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	2,660	17.1
		Stockers and Order Fillers	55.63	2,300	14.8
		Industrial Truck and Tractor Operators	52.30	2,280	14.7
		Packers and Packagers, Hand	67.57	1,870	12.0
		...			
4	Kahului-Wailuku-Lahaina, HI	Waiters and Waitresses	67.21	4,100	53.8
		Maids and Housekeeping Cleaners	100.00	3,210	42.1
		Fast Food and Counter Workers	65.15	2,180	28.5
		Cashiers	54.65	2,160	28.3
		Cooks, Restaurant	70.82	1,980	26.0
		Landscaping and Groundskeeping Workers	71.95	1,650	21.7
		Maintenance and Repair Workers, General	60.60	1,470	19.3
		...			
5	Dalton, GA	Textile Winding, Twisting, and Drawing Out Machine Setters, Operators, and Tenders	78.36	4,530	70.3
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	3,270	50.8
		Cashiers	54.65	1,800	27.9
		Industrial Truck and Tractor Operators	52.30	1,530	23.8
		Customer Service Representatives	56.53	1,350	21.0
		Fast Food and Counter Workers	65.15	1,330	20.7
		Industrial Machinery Mechanics	61.03	1,200	18.6
		...			
6	Ocean City, NJ				
7	San German, PR				
8	Wenatchee, WA				
9	Yuma, AZ				
10	Sebring, FL				
	...				

Table A8: Top Ten States with Highest CAPI

CAPI Rank	Metropolitan Statistical Area	High Potential Occupations	CAPI	Total Employment	The Number of Jobs in the Given Occupation per 1,000 Jobs in the Given Area
1	Nevada	Fast Food and Counter Workers	65.15	43,310	31.1
		Waiters and Waitresses	67.21	37,300	26.8
		Cashiers	54.65	37,060	26.6
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	37,000	26.6
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	29,360	21.1
		Customer Service Representatives	56.53	28,200	20.2
		Maids and Housekeeping Cleaners	100.00	25,140	18.1
		...			
2	Hawaii	Waiters and Waitresses	67.21	19,500	30.7
		Fast Food and Counter Workers	65.15	17,070	26.9
		Cashiers	54.65	13,270	20.9
		Maids and Housekeeping Cleaners	100.00	13,230	20.8
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	11,910	18.7
		Cooks, Restaurant	70.82	11,220	17.7
		Food Preparation Workers	61.15	9,290	14.6
		...			
3	Wyoming	Cashiers	54.65	6,350	23.2
		Fast Food and Counter Workers	65.15	6,000	21.9
		Waiters and Waitresses	67.21	4,740	17.4
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	4,530	16.6
		Maintenance and Repair Workers, General	60.60	3,480	12.7
		Stockers and Order Fillers	55.63	3,300	12.1
		Nursing Assistants	56.34	3,200	11.7
		...			
4	Indiana	Fast Food and Counter Workers	65.15	101,290	33.0
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	93,040	30.3
		Cashiers	54.65	69,340	22.6
		Customer Service Representatives	56.53	53,480	17.4
		Waiters and Waitresses	67.21	49,690	16.2
		Stockers and Order Fillers	55.63	46,490	15.1
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	43,230	14.1
		...			
5	South Dakota	Fast Food and Counter Workers	65.15	13,130	30.9
		Cashiers	54.65	12,550	29.5
		Customer Service Representatives	56.53	8,810	20.7
		Janitors and Cleaners, Except Maids and Housekeeping Cleaners	61.38	8,250	19.4
		Waiters and Waitresses	67.21	7,020	16.5
		Nursing Assistants	56.34	5,990	14.1
		Laborers and Freight, Stock, and Material Movers, Hand	61.05	5,720	13.4
		...			
6	Montana				
7	Wisconsin				
8	Kentucky				
9	South Carolina				
10	Alabama				
	...				