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OCCUPATIONAL EXPOSURE TO ARTIFICIAL INTELLIGENCE BY GEOGRAPHY AND EDUCATION

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Abstract
In this paper we descriptively document the intensity of occupational exposure to artificial intelligence (AI) along two dimensions: geography and education. Along each dimension, we also explore how occupational exposure varies by demographic characteristics. We find that workers in cities are more exposed to AI in their occupations than workers in rural areas on average: AI exposure is four times greater in the most exposed PUMAs (Public Use Micro Areas) compared to the least exposed PUMAs. Workers with at least a bachelor's degree (BA) are also more exposed to AI in their jobs compared to workers without a BA. Among BA holders, STEM and higher-return college majors are among the most exposed, while nursing and education-related majors are among the least exposed. For example, aerospace engineering majors are seven times more likely to be highly exposed to AI in their jobs than special education majors.

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1. Introduction

Recent developments in artificial intelligence appear poised to create large changes in the economy, including through work demanded by employers. But these effects will not be felt uniformly – some workers will be more impacted than others. In this paper, we document variation in AI exposure among workers along two dimensions: geography and educational attainment.

We define occupational AI exposure using work activity data from the Occupational Information Network (O*NET), a product of the Bureau of Labor Statistics (BLS). These data allow us to rank occupations by their anticipated exposure to AI. We define workers in the top quartile of occupational AI exposure as "highly exposed." After briefly outlining how and why we expect AI to impact workers and summarizing the current literature in Sections 2 and 3, Section 4 briefly describes our methodology and Appendix A provides further details. We stress that our measure only identifies "exposure" to AI. The degree to which exposure will translate into positive effects for workers in those occupations (i.e., increase productivity and therefore pay without large reductions in employment) or negative effects (i.e., large reductions in employment and declines in real wages as workers compete with AI) is currently unclear. It is likely some of both will occur.

In Section 5 we provide descriptive statistics showing how our measure of occupational AI exposure varies by demographic and socioeconomic characteristics such as age, race, and education.

In our geographic analysis presented in Section 6, we show that workers in high density areas (i.e., cities) are more likely to work in occupations that are highly exposed to AI. The share of workers in highly exposed occupations is more than four times larger in the most exposed areas than in the least exposed areas. Our results suggest that workers in cities along the northern part of the East Coast are particularly exposed. This relationship may attenuate over time, though, as we find substantial overlap between highly exposed jobs and those that can be done fully from home.

In our educational analysis presented in Section 7, we show large differences in AI exposure by educational attainment, with much higher rates of AI exposure among those with at least a BA. These results are consistent with other studies (e.g., Kochhar 2023). However, the bulk of our educational analysis focuses on differences in AI exposure among BA holders, unlike prior studies. In particular, we document significant variation in occupational AI exposure by field of study (i.e., college major)[1].

At the higher end are STEM majors, such as engineering, which have more than 50 percent of currently working BA holders in highly exposed occupations. At the other extreme, nursing and education majors have very low levels of exposure – less than 10 percent for some majors. Occupational AI exposure for these majors are even lower than average exposure for people

[1] We use the terms "field of study" and "college major" interchangeably throughout this paper to refer to the subject in which the bachelor's degree was earned.

without a BA. Thus, while BA holders are more exposed to AI in their occupations on average, choice of college major is strongly correlated with the degree of AI exposure. Though we are far from the first to note that highly educated workers are more exposed to AI or that certain occupations are more exposed, to our knowledge, we are among the first to highlight the relationship between college major and AI exposure.

In both sets of results, we highlight additional variation in AI exposure by income, race and ethnicity, and sex. For example, we demonstrate that a larger share of workers are highly exposed to AI in locations with high shares of non-Hispanic white workers. Additionally, we show that a disproportionate share of BA-holding Asian workers are highly exposed to AI, even after accounting for higher rates of bachelor's degree receipt among Asian workers than the general population in part because of the college majors and occupations they pursue. Additionally, we show that a disproportionate share of BA-holding Asian workers are highly exposed to AI, even after accounting for higher rates of bachelor's degree receipt among Asian workers than the general population. And while women are more exposed to AI overall, BA-holding men are more exposed to AI in their occupations than BA-holding women, largely due to differences in choice of major and occupation (e.g., women disproportionately select into nursing while men disproportionately select into engineering).

Our results may inform policymakers along a number of dimensions. For example, we find that the most AI-exposed workers are more likely to be high-income, residents of high-income locations, college-educated, and STEM degree-holders. If AI increases the productivity of highly AI-exposed workers without large negative impacts on employment, we anticipate this would exacerbate income inequality. Our geographic analysis may have implications for place-based policies, as the labor markets of cities may be better or worse situated to take advantage of developments in AI. Our educational analysis has implications for optimal education policies (e.g., subsidies), as our results show that the most exposed majors are also the majors with the highest average returns to graduating from college in the first place.

2. Conceptual Framework

In this section, we briefly outline how AI could, in theory, impact work activities, occupations, the geographic concentration of skills, and the returns to education to set the stage for the analysis that follows.

Occupations are composed of many work activities, each of which may be impacted by AI. A worker requires a certain bundle of skills to successfully complete the work activities in a given occupation. As AI impacts work activities, it will shift the demand for skills in the labor market.

Skills and demand for occupations requiring those skills are not uniformly geographically distributed. One reason why some occupations may be in higher demand in some areas is agglomeration – wherein workers are more productive when they are near other workers with similar skills (Goldman, Klier, and Walstrum, 2019). Other explanations may include differences in underlying productivity of the land for various tasks (e.g., manufacturing or agriculture). This geographic concentration of skills and demand for skills explains why there is likely geographic variation in labor market exposure to AI, even if the technology is widely available.[2]

Formal education is one of the primary ways workers acquire the skills necessary to be successful on the job. Higher-paying fields of study are regarded as such because they equip students with skills, both occupation-specific and general, that are highly demanded in the labor market.[3] If AI shifts the demand for skills, the returns to specific educational programs may change as well.

3. Literature Review

While the literature on AI is relatively nascent, several studies have examined the geographic distribution of exposure to AI. Felton, Raj, and Seamans (2021) use occupational data from O*NET to identify occupations exposed to AI and map those occupations to counties.[4] The authors reach similar conclusions as we do – cities are likely more exposed than rural areas, with particularly high exposure from Washington D.C. up to Boston. A report by the Dallas Federal Reserve likewise shows variation in geographic exposure of metro areas (Pranger and Su 2023). The authors speculate that some cities, particularly the most "elite" cities with the highest concentration of the highest skilled workers are likely to benefit from AI (i.e., it will augment the skills of their workers, rather than replace them) compared to less skilled cities where substitution is more likely.

However, the existing literature on the impacts of AI and the returns to obtaining a BA is scant. To our knowledge, there is only one other study that links college majors to AI exposure. Using micro data from Denmark, Humlum and Meyer (2020) examine the "AI relevance" of college majors, which is measured by the share of graduates who work at firms that produce and/or use AI. In the survey used to measure AI relevance, AI is defined as "computer software that 'thinks,' analyzes, solves problems, and recognizes patterns in data." Examples cited by the authors include computer-generated annual reports, chatbots, and automated marketing.

Humlum and Meyer (2020) find that 70 percent of AI-producing firms also use AI but only a third of AI users sell AI-augmented products. The authors use these facts to justify separately considering "AI producers" (those that sell AI-augmented products) and "AI users" (those that use AI but do not produce it). They find that computer science, IT informatics, mathematics, and physics majors are most likely to work in occupations that produce AI, whereas biology, chemistry, pharmaceutical science, molecular biomedicine, biochemistry, and biotechnology majors are among the most likely to work in occupations that use AI. Finally, the authors

[2] To be clear, we make no claims that these geographic differences should be durable – it is quite probable that AI will disrupt the current geographic concentration of skills over time.

[3] We do not mean to imply that we anticipate no supply-side effects of AI on education. Rather, in this brief we focus on the demand side. Appendix C briefly discusses how concentration of fields of study in certain occupations may make those occupations more exposed to labor-supply shocks if AI affects fields of study directly (e.g., makes it easier to get a nursing degree).

[4] Though we also use data from O*NET, our measure of exposure differs Felten, Raj, and Seamans (2021) in that we use O*NETs occupational work activities data while they rely on occupational abilities. Additionally, our sub-state geographic unit of focus is the Public Use Micro Area (PUMA), rather than counties.

provide evidence that majoring in a field of study with high AI producer relevance is positively associated with earnings. In contrast, they find no statistically or economically significant relationship between AI user relevance and earnings.

More broadly, several studies on the potential labor market impacts of AI note that occupations with higher AI exposure are more likely to be held by workers with at least a bachelor's degree. Kochhar (2023) finds that workers with a bachelor's degree or higher are more than twice as likely as workers with a high school diploma only to work in occupations they identify as most exposed to AI. Similarly, Webb (2020) finds that AI exposure is increasing with education, with bachelor's and master's degree holders most exposed.

In addition to impacting the returns to education, AI may influence instruction or, more generally, how skills and knowledge are transmitted and how learning takes place. An analysis of the impact of AI on this component of education is outside the scope of this piece but is an important area for future research.

4. Methodology

To operationalize our analysis, we begin by obtaining the work activities involved with each occupation from O*NET[5] and, following Kochhar (2023), define highly exposed occupations using work activity data.[6]

We group work activities by high, medium, and low exposure to AI based on the anticipated short-term capabilities of new generative AI tools (e.g., Chat GPT-4) following Kochhar (2023). Specifically, when defining the exposure level of each worker activity, Kochhar (2023) and fellow Pew Center analysts ask "What is the likelihood that a work activity may be substitute or complemented by AI at this time? Is the likelihood high, medium, or low?" Kochhar (2023) notes that consensus on some activities was reached quickly. For example, performing general physical activities and processing information were determined to have low and high exposure to AI, respectively. In other instances, the analysts asked the following question to reach consensus: "Are most of the detailed tasks that comprise a work activity exposed to AI?" If most detailed tasks that comprise the broader work activity have a high (low) degree of exposure to AI, the broader work activity was determined to have high (low) exposure.[7] Note that both we and Kochhar (2023) are agnostic about whether AI will act as a substitute or complement for high exposure activities, in part because not all high exposure activities will be impacted in the same manner. We do not have strong priors at this time regarding which high exposure activities will be replaced versus augmented by AI.

After merging the O*NET data with microdata from the American Community Survey (ACS), we follow Kochhar (2023) in defining the most exposed occupations based on their relative share

[5] O*NET is short for the Occupational Informational Network. It is a product of the Bureau of Labor Statistics (BLS).

[6] Appendix A provides more complete details of our methodology.

[7] We note that these classifications are inherently subjective. While we find their classifications reasonable, they are not the only reasonable way to classify AI exposure of work activities. See Webb (2020) for an alternative approach.

of highly exposed work activities to medium- and low-exposed activities.[8] We denote workers in the top quartile of occupational AI exposure as working in a "highly exposed occupation."[9] Appendix Table A.2 contains a list the top 50 most highly exposed occupations. Note that our sample includes only employed workers because we cannot observe a person's occupation (and therefore cannot define their occupational exposure to AI) unless they are employed.

In our geographical analysis, we define geographic exposure based on the share of workers living in an area that are highly exposed to AI.[10] For example, we consider a location where 30 percent of employed persons work in highly exposed occupations to be a more highly exposed geography than one where only 25 percent of employed persons work in highly exposed occupations. We focus on two geographic units. The first geographic unit we consider is states. The second geographic unit we consider is Public Use Micro Areas (PUMAs), which are census-created geographic areas constructed from Census tracts that are designed to contain between 100,000 and 200,000 people; most PUMAs are proper subsets of counties, and all PUMAs are contained within one state.

To conduct our educational analysis, we obtain each worker's field of study from the ACS.[11] These data are available only for those with a at least a BA and only provide information about their bachelor's degree even if they have also earned an associate or graduate degree. College graduates flow into different occupations.[12] Our primary measure of exposure of a field of study to AI is based on the share of graduates currently working in an occupation we consider highly exposed to AI. The higher the share of workers with a given field of study that work in highly AI exposed occupations, the more exposed the field of study. We supplement this measure by also reporting a measure of the concentration of occupations held by graduates of each field, which may impact college graduates' overall exposure to AI if occupations are differentially exposed.

Finally, we note that our methodology has three important limitations. First, our measure identifies the set of workers who we believe are most likely to be *exposed* to AI based on their occupations. It does not and cannot, on its own, speak to how that exposure will translate into productivity gains, changes in employment and wages, etc. Second, our measure of occupational AI exposure is a *relative* (ordinal) measure. Our metric cannot speak to the magnitude of the impacts of being exposed to AI just whether that occupation is likely affected more or less than another occupation. That is, just because we find occupation is 10 percent more exposed does not mean AI will have a 10 percent greater impact on that occupation. Third, we cannot take into account longer-term or general equilibrium effects. For example, it is beyond the scope of our

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[8] See Appendix A for a discussion of some sensitivity tests we performed on our exposure metric. Our results are not very sensitive to exact choice of which tasks are defined as highly exposed but are sensitive to normalizing high- medium- and low-exposure averages.

[9] This accounts for 163 of 494 occupations for which we have data available. Since these occupational groups do not exactly split the sample into fourths, the share of highly exposed occupations as a share of the workforce is slightly over 25 percent.

[10] A worker's location is defined based on her place of residence, not her place of work.

[12] In Section 7, we report results separately for those with more than a BA and those with at most a BA. We note here that graduates of some majors are more likely to attend graduate school, sometimes in a diverse set of fields of subsequent study. We have the most confidence in our estimates for majors where graduate school is less common or where a large share of BA graduates study closely related fields in graduate school. Unfortunately, we are unable to observe field of graduate study in our data.

analysis to consider how AI-induced changes in the returns to education may impact the long-run relative costs of rent in urban areas compared to rural areas as a result of changes in agglomeration. Our results should be viewed primarily as a snapshot of the short run.

5. Descriptive Statistics of Occupational AI Exposure

In this section, we report how the share of workers who are highly exposed to AI varies by demographic and socioeconomic characteristics (see Table 1). As discussed above, by construction approximately 25 percent of workers are highly exposed to AI in their occupations, thus “above average” exposure for a demographic group means more than 25 percent of that subpopulation are highly exposed to AI in their jobs.

Young workers are less likely to be exposed to AI than older workers. Exposure varies much less across age groups over 25, though older workers (55+) are marginally more exposed than prime-age workers (25-54). There is more variation in exposure by race. Hispanic and Black workers are less likely to work in highly exposed occupations than the overall employed population while White and Asian workers are more likely to be exposed.

As discussed in more detail in Section 7, exposure is lowest among those with the least formal education – less 7 percent of workers without a high school diploma are highly exposed to AI in their jobs. Conversely, exposure is greatest for those with a bachelor’s degree or higher. Exposure is also increasing in wages. Workers earning under $75,000 are on average less exposed than the overall population while workers earning more than $75,000 are more exposed than the overall population, with the likelihood of high exposure largest for workers earning over $100,000 per year. On average, workers in highly exposed occupations earn about 29 percent more in wage income than workers who are not highly exposed. This positive relationship between income and occupational AI exposure is discussed further in Sections 6 and 7.

Table 1: Descriptive Statistics of Demographic and Socioeconomic Variation in AI Exposure

	Percent Highly Exposed
Overall	25.4
Age	
<25	18.3
25-34	26.8
34-44	25.8
44-54	25.8
55-64	27.1
65+	28.3
Race/Ethnicity	
White, Non-Hispanic	27.4
Black, Non-Hispanic	21.3
Asian, Non-Hispanic	32.3
Other, Non-Hispanic	25.1
Hispanic	20.4
Education	
<High School	6.6
High School	16.4
Some College	16.0
Bachelor's Degree	36.9
>Bachelor's Degree	31.3
Wage Income	
<$25k	17.3
$25k-50k	21.4
$50k-75k	22.9
$75k-100k	31
$100k+	36.1

Source: ACS (via IPUMS); O*NET. Sample only includes those with positive wage earnings. "Other" race includes, e.g., persons with multiple races. Wage income measured in 2019 dollars. Each cell contains the percent of highly exposed workers within that sub-population, not percent of *all* highly exposed workers that belong to that subpopulation (e.g., 18.3 percent of workers younger than 25 are highly exposed, not 18.3% of highly exposed workers are younger than 25).

6. Variation by Geography in Exposure to AI

6.1 State-Level Variation

Including the District of Columbia,[13] three of the five of the states with the largest share of highly AI exposed workers are along the East Coast from Virginia to New Jersey. In order, they are: The District of Columbia (39.8 percent), Maryland (29.5 percent), Utah (28.1 percent), Colorado (27.6 percent), and New Jersey (27.5 percent).[14] The District of Columbia is a clear outlier

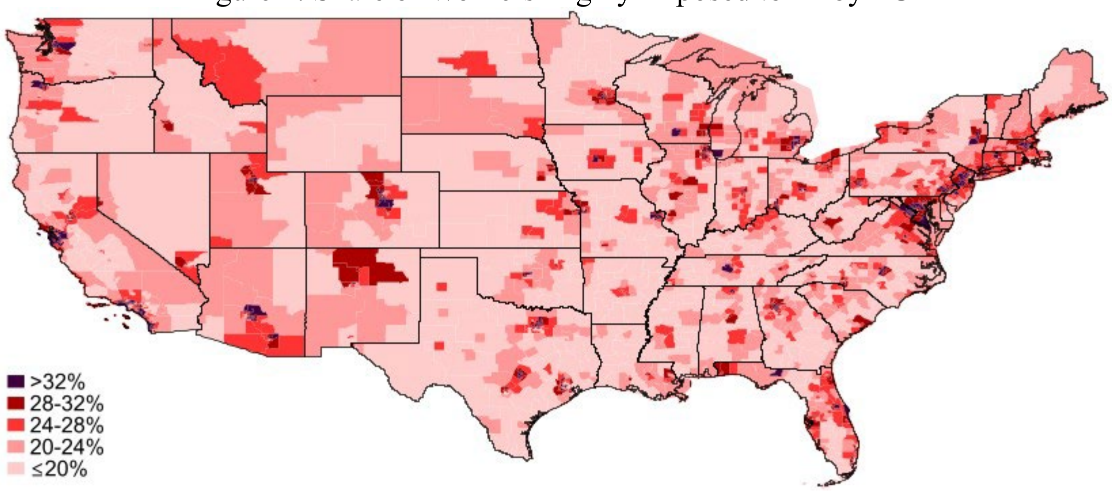
[13] For expositional simplicity when we reference 'states', we include the District of Columbia.
[14] These estimates are based on aggregating from the individual level.

among this group: it both has many clerical and office-type jobs, which are generally highly exposed to AI. D.C. is also highly urbanized, much more than any other state or territory. Still, the (unweighted) average of the remaining top five states (28.2 percent) is about 7.7 percentage points larger than the average of the five states with the lowest share of employment in highly exposed occupations.[15] Variation in AI exposure is larger across smaller sub-state geographies, to which we now turn.

6.2 PUMA-Level Variation

Figure 1 shows shares of employment that are highly exposed to AI, by public use micro areas (PUMAs).[16] Highly exposed PUMAs are geographically concentrated, particularly along the East Coast from Northern Virginia to Massachusetts. Note, since PUMAs are constructed based on population, not geography (e.g., square miles), many PUMAs may be concentrated in a small geographic area. For example, Washington, D.C., contains the same number of PUMAs as both North Dakota and Wyoming, despite having a fraction of the land mass. Of the ten PUMAs with the highest AI exposure, four are in the Washington, D.C., area, and the majority are along the East Coast (see Table 2).

Figure 1: Share of Workers Highly Exposed to AI by PUMA



Source: O*NET, American Community Survey (2021 5-Year ACS), and Kochhar (2023). Highest exposure to AI based on quartile of workers nationally most exposed to AI based on their occupation. Map categories approximately reflect the 25th, 50th, 75th, and 90th percentile cutoffs.

[15] The five states with the lowest shares of highly exposed workers are Mississippi (19.5 percent), Wyoming (20.1 percent), North Dakota (20.7 percent), Arkansas (20.9 percent), and West Virginia (21.3 percent). A full list of all states and their rankings is available in Appendix Table B.1.

[16] As explained briefly in Section 4, PUMAs are constructed from Census tracts. They are proper subsets of states. Each PUMA is constructed to contain at least 100,000 people but no more than 200,000 people. There are about 2,350 PUMAs in total.

Table 2: Ten Most and Least Highly Exposed PUMAs

Rank	State Name	PUMA Name	Share of PUMA Employment Highly Exposed
1	D.C.	District of Columbia (Central)	47.1
2	D.C.	District of Columbia (West)	44.6
3	Virginia	Arlington County (North)	43.5
4	Maryland	Montgomery County (South)	43.1
5	Texas	Houston City (West Central)	42.7
6	New York	NYC-Manhattan Community District 4 & 5	42.3
7	California	Santa Clara County (Northwest)	41.7
8	Illinois	Chicago City (North)	41.3
9	California	Santa Clara County (Southwest)	41.1
10	Georgia	Fulton County (Central)--Atlanta City (North)	41.0
		…..	
2,342	Kansas	Southwest Kansas	13.5
2,343	Missouri	Dunklin, Stoddard, New Madrid, Pemiscot & Mississippi Counties	13.5
2,344	California	Tulare County (Outside Visalia)	13.4
2,345	California	Merced County (West & South)	13.3
2,346	Georgia	Heart of Georgia Altamaha Regional Commission (Southeast)	13.2
2,347	North Carolina	Sampson & Duplin Counties	12.9
2,348	Texas	Houston City (North) & Aldine	12.1
2,349	California	Los Angeles County (Central)--LA City (Southeast/East Vernon)	11.8
2,350	Texas	South Texas Development Council (South)	11.0
2,351	Texas	Hidalgo County (North & West)	10.7

Source: ACS (via IPUMS); O*NET.

Despite being home to two of the highest exposure PUMAs, California only ranks 11th overall at the state level. This is because other PUMAs in California bring down its average. To get a sense of which states have the most variation in highly exposed occupation share across PUMAs, we construct a measure of inequality (relative mean deviation) for each state. This measure helps identify the most homogenous states (least variation in highly AI exposed occupations between their PUMAs) and the least homogenous states. By this metric, the most homogenous states are, in order: Rhode Island, South Dakota, Montana, Wyoming, and Vermont while the most heterogeneous states are, in order: Texas, California, Kansas, Missouri, and Illinois.[17]

[17] Specifically, for each state we calculate the relative mean deviation based on employment shares in highly AI exposed occupations. We weight these results by total employment in each PUMA because, while PUMAs are constructed to have roughly equal populations, populations are not entirely equal. Additionally, roughly equal populations do not imply roughly equal employment (e.g., a PUMA may be home to many retired individuals). We compute similar inequality measures using the Theil entropy index, the Gini coefficient, and mean log deviation. Those measures all approximately agree on the most and least homogenous states, though there is more disagreement in the middle.

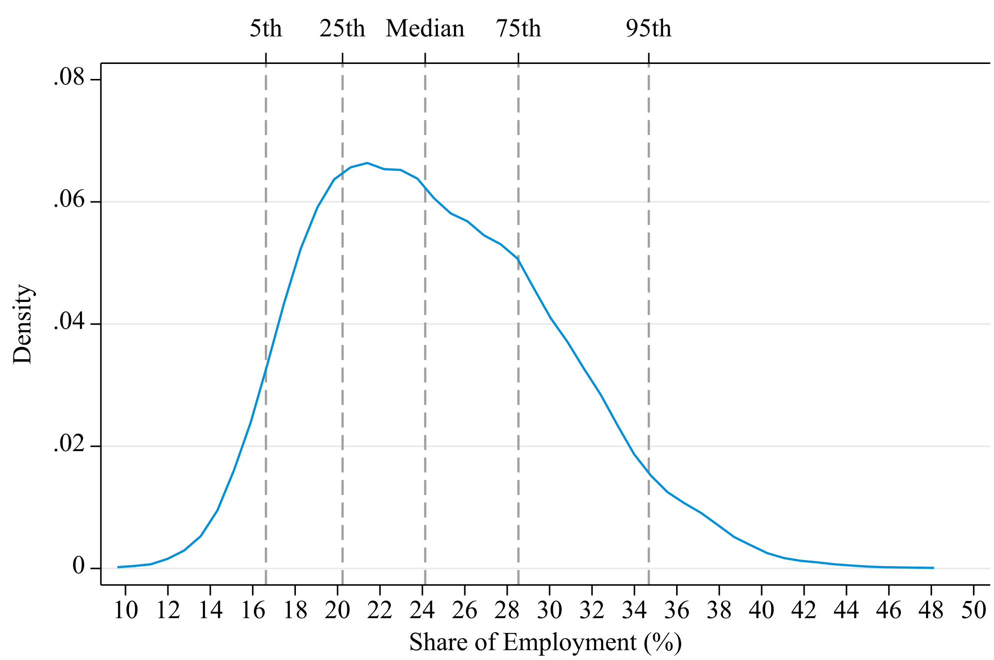
PUMAs with the highest share of highly AI-exposed workers are much more likely to be inside a metropolitan area than PUMAs with relatively low shares of highly AI-exposed workers. Whereas all PUMAs in the top decile of share of workers highly exposed to AI are in metropolitan areas, only 42.8 percent are of the PUMAs in the least exposed decile are in metro areas. Similarly, PUMAs in most exposed decile are more than twice as likely to be in a central or principal city as a PUMA in the least exposed decile.

Table 3: Share of PUMAs in Metro Areas by Share Highly Exposed to AI

Decile of Highly AI Exposed Share	% PUMAs in a Metropolitan Area	% PUMAs in Central/Principal City
Bottom	42.8	12.3
2	44.7	7.2
3	55.3	9.4
4	73.6	8.5
5	89.8	14.5
6	93.6	14.0
7	98.3	12.3
8	99.6	11.5
9	99.6	14.0
Top	100.0	27.2

Source: ACS (via IPUMS); O*NET

Figure 2: PUMA-Level Kernel Density Estimates of Share of Employment in Occupations Highly Exposed to AI



Notes: Based on an Epanechnikov kernel density estimator with bandwidth of 1.070. Data from BLS, ACS, and Kochhar (2023). Gray dashed lines correspond to percentiles of the employment share distributions.

There is variation between PUMAs in AI exposure. As Figure 2 shows, approximately 24 percent of workers in the typical (median) PUMA are highly exposed to AI.[18] The 25th percentile of AI exposure is 20.3 percent, and the 75th percentile is 28.5 percent. Five percent of PUMAs have an exposure of more than 34.6 percent.

6.3 Characteristics of Highly Exposed PUMAs

There is a statistically positive correlation between (log) density (persons per square mile) and high AI exposure (see Figure 3).[19] A doubling of PUMA density is associated with a roughly 1.6 percentage point higher share of employment in highly AI exposed occupations.[20] Stated alternatively, moving from the 5th percentile of density to the 95th percentile of density is associated with a 8.2 percentage point higher share of employment in highly AI exposed occupations, which does not fully account for the variation in AI exposure overall. Thus, density is plausibly economically significant, but hardly the singular dominant factor in the observed variation in highly AI exposed workshare by PUMA.[21] As noted in Section 2, there are several potential reasons for the existence of this statistical association, including greater agglomeration effects for highly exposed occupations. That said, these estimates should not necessarily be interpreted causally, and there may be other explanations for the link between density and AI exposure.

At the PUMA level, the share of employment in highly AI exposed occupations is positively correlated with the share of the non-Hispanic white population and average PUMA wage income (see Figure 4). These associations remain statistically positive even after controlling for each other, population density, and time-invariant state-specific factors.[22] Although average age of workers in the PUMA is positively associated with the share of workers that work in highly exposed occupations, the reverse is true after controlling for (log) wage income and (log) density, suggesting income and density capture much of the same variation captured by the raw correlation of average age and AI exposure.[23]

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[18] As explained in the methodology section, the national mean share of workers highly exposed to AI is about 25 percent by construction.

[19] See Appendix Figure B.1 for an un-binned scatterplot. As a robustness check, Figure B.2 reports an un-binned scatterplot of AI exposure versus density, rather than log density.

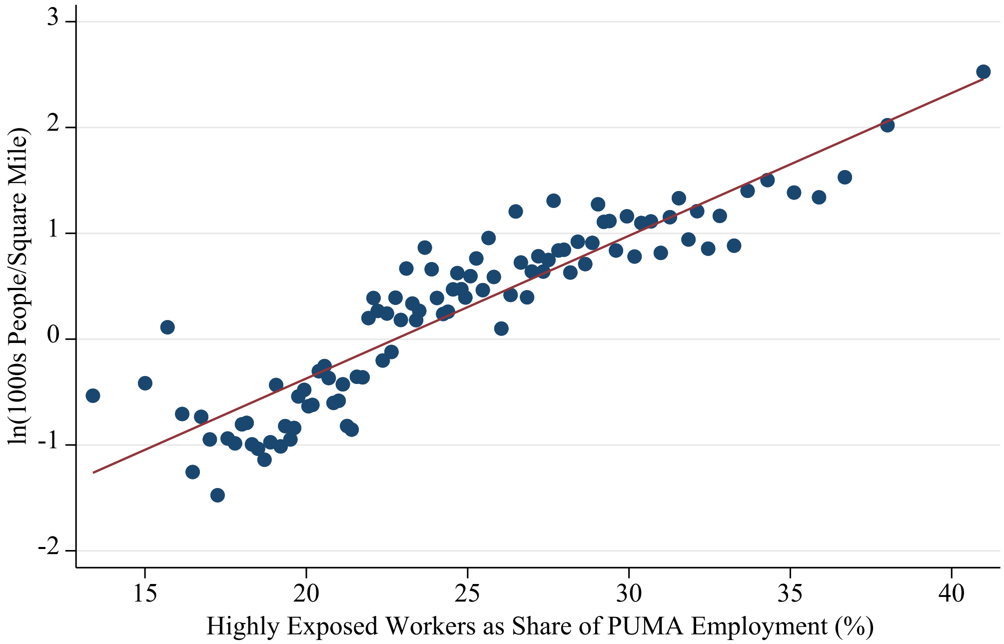
[20] Specifically, a linear regression of (high AI exposure) against the natural log of density, with state fixed effects and clustered by states, is statistically positive (p<.001) with a point estimate on ln(density)=1.551. The standard deviation of high exposure employment share is about 5.6. Note: Figure 3 shows the raw correlation between log density and AI exposure.

[21] The R^2 of the regression described above is about 0.27; the R^2 of a regression of AI exposure against log density, without more, is about 0.21.

[22] Specifically, when estimating the regression $popshare_{sp} = \beta_1 \ln(density_{sp}) + \beta_2 \ln(income_{sp}) + \beta_3 WhiteShare_{sp} + \alpha_s + \epsilon_{sp}$ for PUMA p in state s and state fixed effects α_s, the coefficients β_2 and β_3 are both statistically positive (p<.01) even after clustering standard errors at the state level. Based on raw correlations, non-Hispanic white share is better described as a quadratic function, but the same is not true after including controls.

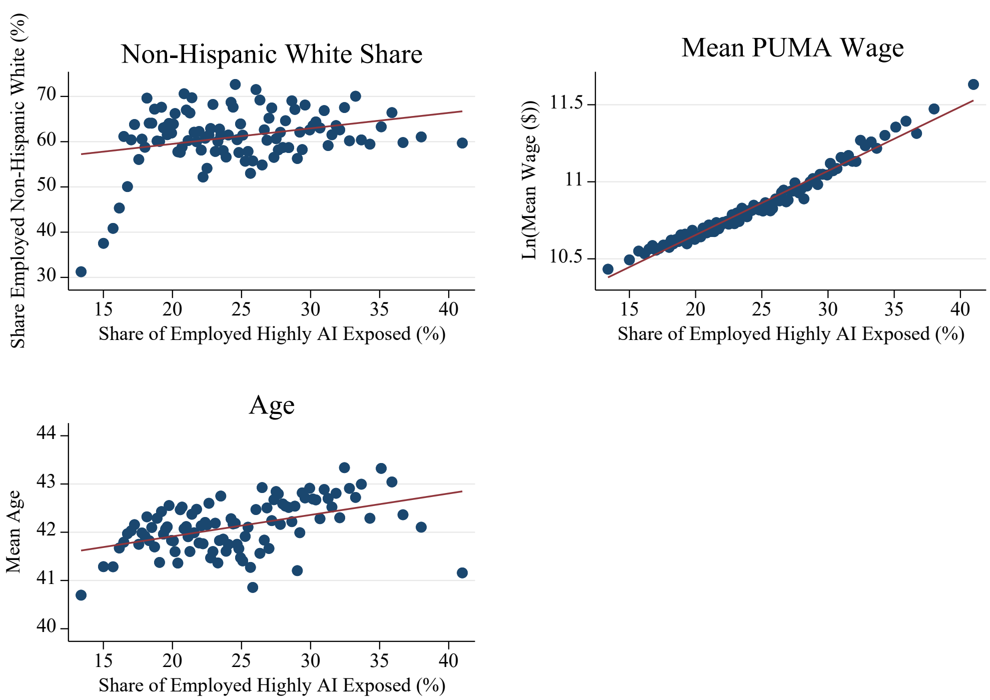
[23] Figure 4 show raw correlations. Figure B.3 in the Appendix shows residualized binned scatter plots (i.e., controlling for some other factors).

Figure 3: Correlation Between High AI Exposure and Density



Notes: Data from BLS, ACS, and Kochhar (2023). PUMA = Public Use Micro Area. This figure shows a binned scatterplot, mapping each percentile of the highly exposed worker share against the average log density of approximately 23 PUMAs per percentile. Red line is a line of best fit.

Figure 4: Correlations Between High AI Exposure and Demographic Characteristics



Source: O*NET, ACS (via IPUMS), and Kochhar (2023).

6.4 Remote Work

In this subsection, we demonstrate that there is substantial overlap in occupational AI exposure and the likelihood that a job can be done remotely, and, consequently, the geographic distribution of highly exposed jobs and the geographic distribution of "teleworkable" jobs. Workers in jobs that can be done fully remotely may have fewer geographical constraints, which may in turn have implications for the geographic distribution of highly exposed workers described above and its impacts on local economies.

To determine the relationship between AI exposure and the "teleworkability" of jobs, we merge our measure of AI exposure with Dingel and Neiman (2020)'s occupation-specific characterization of whether work can be performed fully remotely. Based on their classifications, we estimate that about 42% of jobs in our sample can be performed entirely at home.[24] We find that a little under 20% of all jobs are both highly exposed to AI and can be performed entirely remotely. By construction, about 25% of all jobs are classified as highly exposed to AI, so we find that about 78% of jobs highly exposed to AI can also be done fully remotely. Note, just because a job *can* be done fully remotely does not mean workers in fact *do* work fully remotely. A February 2023 Pew Poll found approximately 40 percent of workers say their job can be done mostly from home but only about a third of those workers report working exclusively from home (Parker 2023).

Examples of highly exposed occupations that can be done fully remotely include data entry keyers, computer programmers, and customer service representatives. Examples of highly exposed occupations that cannot be done fully remotely include receptionists and information clerks as well as construction and building inspectors.[25] In Appendix Table B.2 we report whether some of the largest (by employment) highly exposed occupations can be performed fully at home or not. There is a strong correlation between PUMA-level exposure to AI and share of jobs by PUMA that are teleworkable, with a correlation coefficient of 0.94. That said, the strong correlation documented above between PUMA-level occupational AI exposure and PUMA-density is much stronger for highly exposed occupations that can be performed at home than occupations that are highly exposed and cannot be done at home.[26] Stated differently, almost all the observed variation between PUMA-level exposure to AI and density is explained by variation in exposure among occupations that could be done fully remotely.

[24] This estimate is slightly higher than Dingel and Neiman (2020)'s estimate of 37%. These differences may be attributable to several factors, including that we use more recent data from 2017-2021 and our underlying data for employment estimates (ACS) is different than their source (Occupational Employment and Wage Statistics).
[25] We use Dingel and Neiman (2020)'s O*NET derived estimates of whether work can be done from home. They note that their O*NET derived measures are inconsistent with their priors for several occupations, including some that we classify as highly exposed but not capable of being done fully from home including travel agents and tax examiners.
[26] More formally, the correlation between log density and share of employment highly exposed to AI in a PUMA (regardless of remote-work status) is 0.4585 whereas it is 0.4889 for log density and highly exposed to AI and fully remote work is possible and 0.1087 for highly exposed to AI and fully remote work not possible. Likewise, a regression of employment share highly exposed to AI where work can be fully remote against log density results in an R^2 of .2391 compared to an R^2 of only 0.01118 for a corresponding regression where the dependent variable is share of highly AI exposed workers working in jobs where working fully remote is not possible. The model is significant for the former at the 1% significant level even after clustering standard errors at the state level while it is not for the latter.

The strong correlation between occupational AI exposure at the PUMA level and share of teleworkable jobs provides an important cautionary note for interpretation of our geographic analysis. Namely, since highly exposed workers are much more likely to work in occupations that can be done entirely from home, they may also be more geographically mobile – less tethered to one location by their job. And while there is currently a strong correlation between density and AI exposure, that may change if jobs that *could* be done from home become fully remote in the future, allowing them to move.

We recognize that the interaction between remote work and occupational exposure to AI likely extends beyond the narrow geographic lens we have focused on in this subsection. For example, it may well be that highly exposed jobs that can be done fully remotely are at a differential risk of being "replaced" by AI compared to jobs with an in-person component. And it may be that developments in AI assist in narrowing the gap between work that could be done remotely but currently is not. Though important questions, we leave them for future research.

7. Variation by Educational Attainment in Exposure to AI

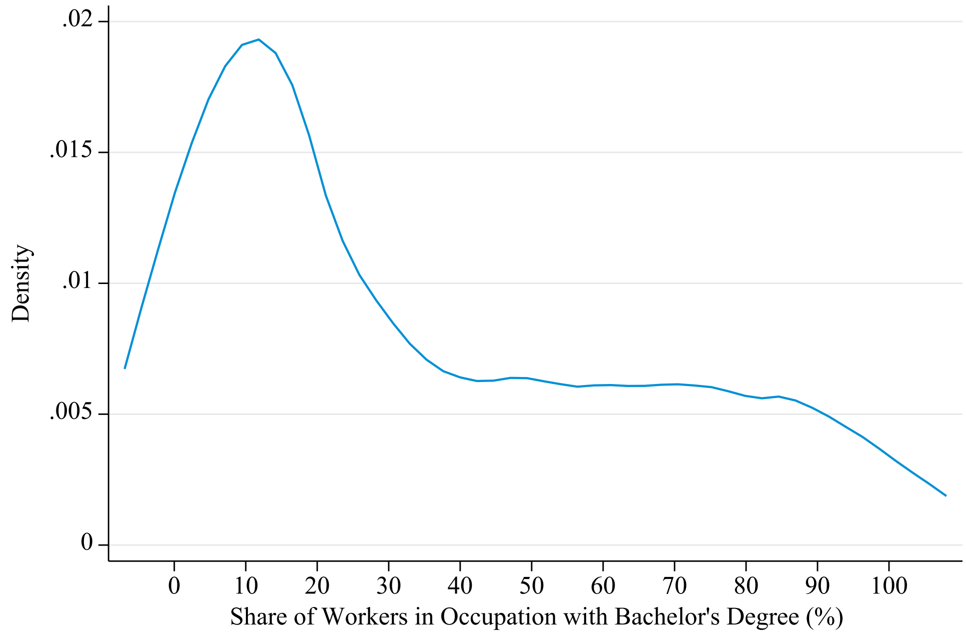
7.1 Why Focus on BA Holders?

In this section, we document variation in occupational exposure to AI based by educational attainment. We focus on bachelor's degree holders and note at the outset that they are relatively uncommon in most occupations in our data and in the United States as a whole. In 2022, 37 percent of Americans 25 and older had earned a bachelor's degree or higher (Census 2023). We find that fewer than 30 percent of workers have a BA in most occupations; it is more common for 5 percent to 15 percent of workers in an occupation to have a BA than it is for more than 65 percent of workers in an occupation to have a BA (see Figure 5).[27]

However, we find, as others have, that workers in occupations most exposed to AI are much more likely to have at least a BA. Whereas BA-holding workers comprise the majority of workers in fewer than 10 percent of the least exposed occupations, they comprise a majority in approximately 50 percent of the most exposed occupations (see Figure 6). Therefore, even though college degrees are uncommon in many occupations, they are extremely common in the that occupations we anticipate will be most affected by recent AI developments, at least in the short run.

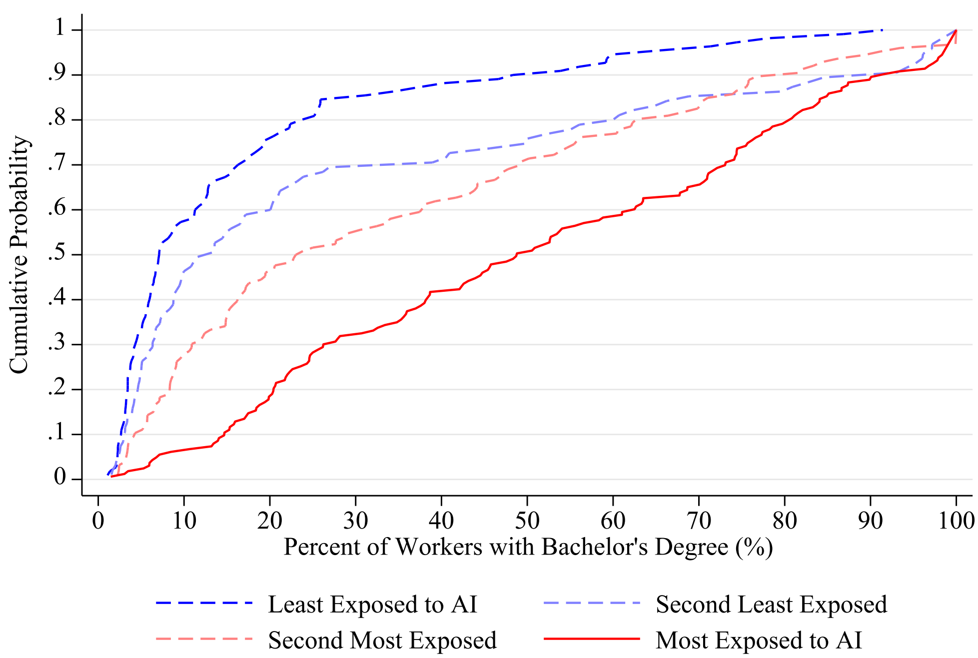
[27] We note that Figure 5 is not population weighted. Just under a third (~32 percent) of workers have occupations where the share of workers with a BA is between 5 percent and 15 percent, and just over a fifth of workers (21 percent) have occupations where at least 65 percent of workers have a BA.

Figure 5: Share of Workers with BAs or Higher, by Occupation



Source: American Community Survey. Sample only includes employed workers with known occupations that could be matched to O*NET data. Density estimates constructed using Epanechnikov kernel.

Figure 6: Cumulative Share of Workers with BAs, by AI Exposure



Source: American Community Survey, O*NET. Note: Each occupation given equal weight within each category.

7.2 AI Exposure by Field of Study

Next, we examine the fields of study of BA holders working the highest and least exposed occupations. We define the most exposed fields of study as those with the largest shares of currently employed bachelor's degree holders working in highly AI exposed occupations. We caution that our measure only captures the primary field of study for a person's bachelor's degree – professionals such as lawyers, doctors, and PhD researchers are captured only to the extent that they tend to also hold undergraduate degrees.[28]

Engineering fields are among the most highly exposed fields, while education fields are among the least highly exposed (See Table 4).[29] In general, the most highly exposed fields are also those categorized as STEM whereas non-STEM majors are less exposed.[30] Notably, nearly very few (6 percent) of the graduates in nursing work in a highly exposed occupation. This is because by our definition of AI exposure, nursing is not a highly exposed occupation, and the large majority of nursing graduates become nurses.

Not all occupations are like nursing: just because a large share of graduates of a particular field of study work in highly exposed occupations does not mean they work in the *same* occupation. In Figure 7, we plot the share of workers in a given field who are highly exposed to AI against the Herfindahl-Hirschman Index (HHI) of the 494 occupations we consider.[31] Higher values of HHI in this context mean a large share of graduates of a particular field of study flow into the same occupation.[32]

Overall, occupational flows by field of study are not highly concentrated (as seen by a clustering of many fields of study with low HHI), though there is a u-shape relationship to concentration by the share of graduates working in highly exposed occupations. That is, the fields of study that send graduates into a narrow set of occupations tend to be fields of study that either have a very large or very small share of workers working in a highly exposed occupation. Heavy concentration into a narrow set of fields is at least suggestive that the skills a worker learns in their field of study are not as broadly valued by or transferable to other occupations. As a result, workers with degrees that flow heavily into a narrow set of occupations may be especially affected by occupation-specific shocks induced by AI.

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[28] We define a person's primary field of study as their response to "degfieldd" in IPUMS's ACS codes. A minority of survey respondents report having two fields of study (i.e., likely were double majors).

[29] See Table B.3 in Appendix B for a complete list of fields reported in Table 4. See Table B.4 for a complete list using broad categories of fields instead of the detailed codes reported in Table 4.

[30] STEM is an acronym for Science, Technology, Engineering, and Math. We derive our classification of whether a field of study is a STEM major from the Department of Homeland Security's STEM Designate Degree Program List.

[31] HHI is the sum of squared shares (in this case of fields of study by occupation) expressed as percentages. The higher the HHI, the more concentrated. An HHI of 10,000 implies all graduates of a field of study flow into just one occupation.

[32] We recognize that AI may change these major-occupation flows over time, but we refrain from speculating how and instead take current major-occupation flows as given.

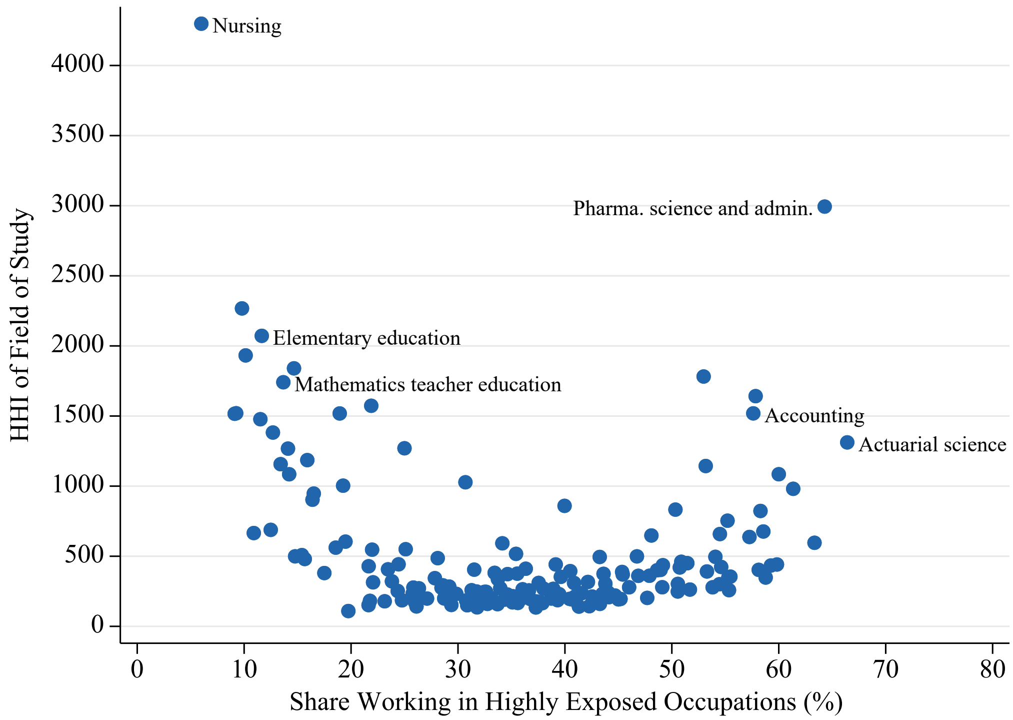
Table 4: Ranking of Fields of Study by Share in Highly AI Exposed Occupations

Rank	Field of Study	STEM field?	% in Highly Exposed Occupations
1	Actuarial science	Yes	66
2	Pharmacy, pharmaceutical sciences, and administration	Yes	64
3	Aerospace engineering	Yes	63
4	Architecture	No	61
5	Civil engineering	Yes	60
6	Mechanical engineering	Yes	60
7	Environmental engineering	Yes	59
8	Computer information management and security	Yes	59
9	Atmospheric sciences and meteorology	Yes	59
10	Architectural engineering	Yes	58
	…		
164	General education	No	13
165	Educational psychology	No	12
166	Elementary education	No	12
167	Early childhood education	No	12
168	Treatment therapy professions	No	11
169	School student counseling	No	10
170	Teacher education: multiple levels	No	10
171	Special needs education	No	9
172	Educational administration and supervision	No	9
173	Nursing	No	6

Source: ACS, O*NET. Sample only includes employed workers. STEM= Science, Technology, Engineering, or Mathematics. STEM or non-STEM designations based on the Department of Homeland Security's STEM Designated Degree Program List.

Even the most highly exposed fields by our metrics have some graduates who flow into less highly exposed occupations. That said, it is rare for a field of study to have both a large share of graduates flowing into highly exposed occupations and a large share of graduates flowing into the least exposed occupations. Highly exposed occupations represent the largest share of employment in approximately half (96/172) of the fields of study we consider. In approximately 97 percent (93/96) of those occupations where the largest share of workers belong to highly exposed occupations, the second largest share of workers belong to the second most highly exposed occupations. That is, in fields where graduates are highly likely to work in a highly exposed occupation, their likeliest alternative occupation is still in a fairly highly exposed occupation.

Figure 7: Concentration of Occupational Flows vs. Occupational AI Exposure



Source: ACS, O*NET. Each dot represents a field of study. HHI concentration based on occupations graduates of that field of study now work in. Large values of HHI indicate a large share of graduates in that field work in a small set of occupations.

7.3 Demographic Variation in AI Exposure

Next, we examine occupational exposure to AI by race and ethnicity and sex for college graduates and those without a college degree. Among college graduates, we document variation in occupational AI exposure across both demographic groups and fields of study.

7.3.1 Race and Ethnicity

We find, as other have (e.g., Kochhar 2023), that Asian and non-Hispanic white workers are more exposed to AI in their occupations than workers in other racial and ethnic groups (see Table 5). Using our measure, Asian and non-Hispanic white workers are, respectively, about two and seven percentage points more exposed to AI in their jobs than the overall population while Hispanic and Black workers are, respectively, about six and three percentage point less likely to be exposed to AI in their jobs.

We find that there is comparatively less variation in AI exposure by race and ethnicity among college graduates than the overall population. Whereas non-Hispanic white workers are more than eight percentage points likelier to be highly exposed to AI than Hispanic workers, the difference shrinks to less than four percentage points among college graduates. These differences are partially due to differences in educational attainment, but not entirely. Asian workers are not only more likely to have a college degree than other populations, but college-educated Asian workers are more likely to work in an occupation that is highly exposed to AI than BA holders of any other racial or ethnic group that we consider.

Table 5: AI Exposure by Race/Ethnicity and Education

Race/ Ethnicity	Overall	Not College Graduates	College Graduates
Hispanic	19.1	15.9	32.2
Black	22.3	17.6	31.4
Asian	32.2	18.7	42.4
Non-Hispanic White	27.4	22.5	35.6

Source: ACS, IPUMS, O*NET. College graduate in this table means has a bachelor's degree or higher. Sample includes workers with positive wage earnings.

In our sample, Asian and Hispanic workers each represent approximately 10 percent the college-educated workforce (with positive earnings) and Black workers represent about 9 percent. Among the 34 fields where a majority of workers are employed in highly AI exposed occupations, Asian workers are overrepresented in 24 fields, Hispanic workers are overrepresented in 14, and Black workers are overrepresented in 7 fields.[33] This highlights how Asian workers are not only more likely to work in highly AI exposed occupations, but they are also much more likely to have earned a degree in a field that is highly exposed to AI.

7.3.2 Sex

We examine differences in AI exposure by sex in a similar manner. Overall, we estimate that females are more likely to be highly exposed to AI in their occupations than males. However, among BA holders, the reverse is true. The difference is due to the dramatic difference in occupational exposure of BA-holding men compared to non-BA-holding men. As Table 6 shows, BA-holding men are almost three times more likely to work in a highly AI exposed occupation than non-BA-holding men. By contrast, the disparity among BA- holding and non-BA-holding women is much smaller.

Table 6: AI Exposure by Sex and Education

	Overall	Not College Graduates	College Graduates
Male	21.9	13.5	38.9
Female	29.2	28.1	31.1

Source: ACS (IPUMS), O*NET. Sample includes employed workers with positive earnings.

The differences in occupational AI exposure among BA holders is not (fully) driven by differences in occupational flows by major, but rather differences in major in the first place. For example, the share of nursing majors working in highly exposed occupations is around 6 percent

[33] Appendix Table B.5 provides a detailed breakdown of these results.

for both men and women, but, as Table 7 shows, women are seven times (1/.14) more likely to have majored in nursing in the first place. Likewise, more than 60 percent of mechanical engineering majors work in highly AI exposed occupations regardless of sex, but men are almost ten times more likely than women to major in mechanical engineering.[34]

Table 7: Differences in Major Choice by Sex for Top 25 Most Popular Majors

Field of Study	% AI Exposed	Ratio Share Men vs Share Women
Nursing	6	0.14
Elementary education	11	0.13
General education	12	0.36
Physical fitness, parks, recreation, and leisure	22	1.28
Psychology	26	0.43
Biology	28	0.96
Liberal arts	30	0.73
Sociology	32	0.55
Criminal justice and fire protection	32	1.59
English language and literature	34	0.59
History	35	1.87
Communications	37	0.71
General business	38	1.60
Business management and administration	38	1.29
Mathematics	38	1.52
Marketing and marketing research	39	0.92
Economics	42	2.36
Political science and government	46	1.61
Finance	46	2.26
General engineering	51	6.18
Computer science	54	3.28
Accounting	57	1.03
Electrical engineering	59	7.07
Mechanical engineering	60	9.70

Source: ACS (IPUMS), O*NET. Ratios reflect the relative likelihood of a BA-holding man majoring in a field compared to a BA-holding women majoring in that field. The numerator is the share of men in a field as a percent of all BA-holding men. The denominator is the same, but for women. A value of .5 means women are twice as likely to major in that field. A value of 2 means men are twice as likely to major in that field.

[34] More generally, we find the share highly exposed by major for men is highly correlated with the share highly exposed by major for women – a correlation coefficient of about .93.

7.4 Additional Estimates

7.4.1 Income and the Returns to Education

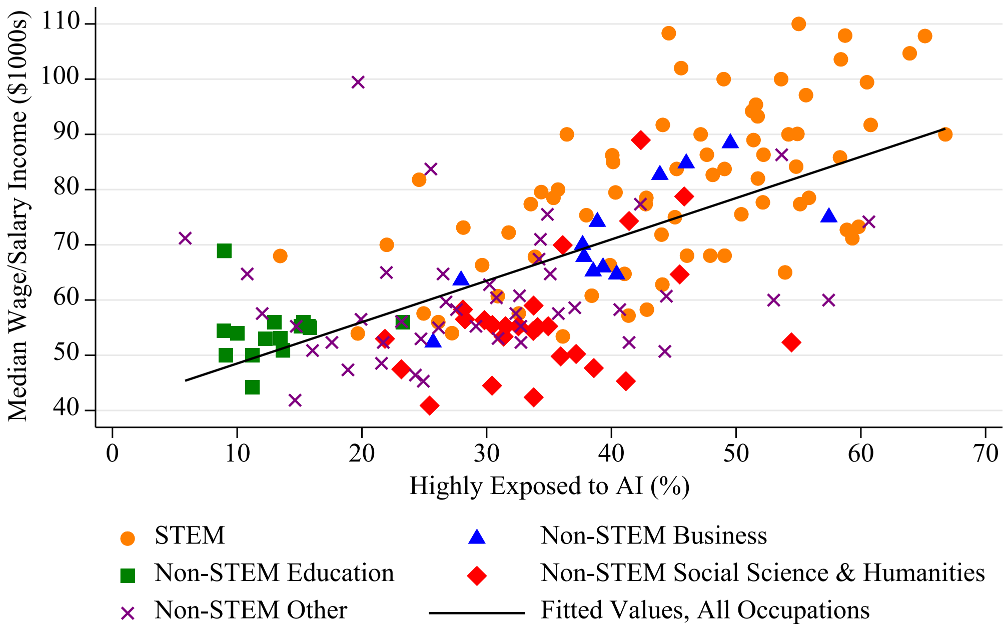
Previous research (Kochhar 2023) has suggested higher income individuals are more likely to be exposed to AI in their jobs. We find the same is true by field of study – that is, we find occupational AI exposure is, on average, higher in fields of study with higher median incomes among BA holders.

In Figure 8 we plot occupational AI exposure by field of study against median wage income for BA holders of that field. For example, the typical (median) early childhood education major earns about $47,000 a year and 11 percent are highly exposed, compared to $118,000 and 60 percent, respectively, for mechanical engineers. More generally, STEM majors are, on average, much more likely to be highly exposed to AI but also have higher incomes. Conversely, we find that education majors tend to have low occupational AI exposure but also low incomes. Those majoring in most of the social sciences and humanities majors have higher exposure, but, on average, comparable incomes to education majors, who are less likely to be highly exposed.[35]

The positive correlation between the returns to college majors and occupational exposure to AI may prove important because it highlights how developments in AI use may compress or exacerbate the inequality in returns to a bachelor's degree.[36] While the raw correlations reported in Figure 8 do not show the (*net) returns* to education, they are consistent with previous studies that find certain majors have higher net returns (i.e., engineering) than others.[37]
The positive correlation between returns to college majors and AI exposure suggests that developments in AI may compress (expand) inequality in returns to education if AI tends to substitute (complement) work done in these high-income occupations. It likewise means that AI will affect the average returns to education, possibly changing the optimal allocation of public subsidies toward higher education.

[35] By "Social Sciences & Humanities" we specifically mean those majoring in linguistics and foreign languages (degfield==2600; english and literature (degfield==3300); Liberal arts and humanities (degfield=3400); library science (degfield=3500); general social sciences (economics, sociology, etc.) (degfield=5500); and fine arts (degfield=6000).
[36] See, e.g, Altonji and Zimmerman (2019) for an example of how returns differ by major, even after controlling for differential cost of attendance. See also Krueger (1993).
[37] See, e.g, Altonji, Blom, Meghir (2012).

Figure 8: Correlation Between AI Exposure and Median Income by Field of Study



Source: ACS (via IPUMS), O*NET, DHS. Sample includes employed BA holders with positive earnings and a known field of study. Occupations classified as STEM included in STEM even if they fit in other categories as well. "Non-STEM Other" includes majors like communications and various non-STEM medical sector majors, like nursing.

7.4.2 Advanced Degrees

Approximately 40 percent of college graduates in our sample have earned a degree beyond a bachelor's degree, such as a master's degree or doctorate degree. Two thirds of those with more than a bachelor's degree hold a master's degree. We are unable to directly observe field of study in graduate school in our sample, but we can observe the highest level of educational attainment.

In Table 8 below we replicate Table 4, splitting the sample between those with at most a bachelor's degree and those with a master's degree or higher. There are broad similarities in the least exposed undergraduate fields of study – nursing and education near the bottom for both subsamples. Large shares of those who study engineering, both those who stop at the undergraduate level and those who continue on to graduate school flow into highly exposed occupations. A substantially higher share of those with graduate degrees who earned their undergraduate degree in pre-law and legal studies work in highly exposed occupations (64 percent) than those who did not obtain a graduate degree after studying pre-law and legal studies (54 percent). Those with no more than a bachelor's degree are more likely to work in a highly exposed occupation than those with a master's degree or higher (37 percent compared to 32 percent, respectively); though both groups are much exposed than those with less than a bachelor's degree (20 percent) or those with an associate degree (28 percent).[38]

[38] Based on highest educational attainment. While we observe associate degree status, our data do not allow us to observe the field of study for associate degree recipients.

Table 8: Most Exposed Fields of Study by Level of Educational Attainment

	No More than BA		More than BA	
Rank	Undergraduate Field of Study	% Highly Exposed	Undergraduate Field of Study	% Highly Exposed
1	Actuarial science	69.4	Pre-law and legal studies	64.0
2	Aerospace engineering	66.7	Pharmacy, pharmaceutical sciences, and administration	63.5
3	Pharmacy, pharmaceutical sciences, and administration	65.4	Architecture	63.3
4	Mechanical engineering	62.3	Architectural engineering	62.3
5	Environmental engineering	61.7	Petroleum engineering	60.0
6	Nuclear engineering	60.7	Aerospace engineering	59.9
7	Civil engineering	60.5	Civil engineering	59.2
8	computer information Management and security	60.4	Geosciences	59.0
9	Architecture	60.1	Communication disorders sciences and services	58.7
10	Atmospheric sciences and meteorology	59.2	Accounting	57.9
	…		…	
164	General education	15.6	General education	9.5
165	Elementary education	15.1	Treatment therapy professions	9.2
166	Medical assisting services	15	Educational psychology	9.0
167	Cosmetology services and culinary arts	14.4	School student counseling	8.9
168	Early childhood education	14.2	Educational administration and supervision	8.6
169	Treatment therapy professions	12.4	Elementary education	7.8
170	Teacher education: multiple levels	12.3	Special needs education	7.3
171	Special needs education	12.2	Early childhood education	7.1
172	Nuclear, industrial radiology, and biological technologies	11.6	Teacher education: multiple levels	7.1
173	Nursing	5.7	Nursing	6.7

Source: ACS (via IPUMS), O*NET.

8. Conclusion

Recent developments in AI have the potential to affect wide swaths of the economy. In this paper, we focus on identifying geographies and subsets of workers that are most likely to be affected by recent AI developments. We begin by showing that older workers are more likely to work in highly exposed occupations than younger workers and that White and Asian workers are more likely to be exposed than Hispanic and Black workers.

We then document large variation in geographic concentration of AI exposed workers and find that the highest concentration of AI exposed workers live in high-density areas, areas with large non-Hispanic white population shares, and high-income locations. We also find that the most highly exposed occupations are more “teleworkable” – i.e., able to be done from home – suggesting that the geographic patterns we document could shift if fully remote workers decide to relocate.

We additionally expand on previous findings that bachelor’s degree holders are more exposed to AI by showing that there is large variation in AI exposure among 4-year college graduates, including by college major, sex, race, and income. STEM majors are among the most highly exposed, and, on average, more highly exposed fields of study tend to be higher-paying fields. We find that a disproportionate share of BA-holding Asian workers are highly exposed to AI and that BA-holding men are more exposed to AI in their occupations than BA-holding women, largely due to differences in choice of major and occupation.

The purpose of this analysis is to advance discussions of the potential labor market and economic impacts of AI. Although we cannot speak to the scope of those impacts at this time, this work lays the groundwork for further analysis of the heterogeneous impacts of AI in the labor market and potential policy responses as the technology matures.

The policy implications of our analysis depend on whether AI will be primarily used to replace or complement labor. If AI replaces labor more than complements it, our results suggest that wage income inequality between typical workers in urban and rural areas will decline, though some “elite” cities may become even more productive (Pranger and Su 2023). In addition, variation in the returns to college majors may narrow due to declines among high-return and highly exposed majors like engineering. Similarly, the relative returns to higher education may decline, perhaps suggesting different optimal subsidization for higher education. Sex and racial wage income gaps may decline as well.

However, the extent to which AI replaces versus complements labor is unlikely to be uniform, and it is likely that inequality and income gaps may narrow in some areas and among some segments of the population and widen in others. This could plausibly happen even within occupations: as some workers are replaced, the remaining workers may become more productive – implying an increase in income inequality between the “AI winners” and “AI losers” within the same occupation. Future research is needed as AI develops to continue documenting the distributional impacts of exposure to AI and to quantify its effects on the labor market.

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APPENDIX A: Methodology

Our methodology mostly follows Kochhar (2023), except we use worker data from the American Community Survey (ACS) instead of the Current Population Survey (CPS). Using the ACS, we can analyze smaller geographic units and use a more finely defined occupational codes than are available in the CPS. We also use a more recent version of O*NET data, 28.0, while they use O*NET 27.3.

First, based on Kochhar (2023), we assign the 41 work activities found in O*NET to high, medium, or low exposure to AI. These assignments are inherently subjective, but we determined Kochhar's assignments to be reasonable. For example, we think that the task "Processing information" is appropriately considered a high AI exposure work activity and the task "Assisting and caring for others" is appropriately considered a low AI exposure work activity. See Appendix Table A.1 for a full list of the 41 work activities and their designations.[39]

Next, we merge work activity classifications to O*NET's 6-digit Standard Occupational Classification (SOC) codes.[40] These codes contain detailed occupational data, including the importance of each activity to each occupation, typically based on interviews the Bureau of Labor Statistics conducted with incumbents in that occupation. Not all occupations have work activity data – The O*NET 28.0 database contains work activity data for 873 out of 923 occupations.[41]

O*NET classifies each activity by its importance for each occupation on a scale from 0 to 7. We then take the average importance rating for high, medium, and low exposure activities to obtain an aggregate importance rating for each group of work activities. This gives us the average importance (from 0 to 7) of high-, medium-, and low- exposure work activities for each occupation. We then normalize these measures to get the relative importance of each group of activities for each occupation. For example, the relative importance of high, medium, and low exposure activities in an occupation be 30, 30, and 40 percent, respectively.[42,43] Appendix Table

[39] As a robustness check, we experimented with two alternative definitions of high-exposure work activities based on a subset of the 16 high-exposure tasks laid out by Kochhar (2023) and found that our results are not particularly sensitive to whether Kochhar (2023) full set of high exposure activities or a subset are used. Two alternative specifications using the author's subjective determinations of the subset of "most exposed" work activities were highly correlated with the metric based on Kochhar (2023)'s definition, with Spearman Rank Correlation coefficient of about .6 with a p value less than .0001 for highly exposed occupations.
[40] https://www.onetcenter.org/taxonomy.html
[41] Occupations missing work activity data are primarily those classified as "all other" occupations (e.g., SOC code 13-1199.00 "Business operations specialists, all other"); however, O*NET data also exclude software developers, who we anticipate would otherwise likely have otherwise been classified as highly exposed to AI. BLS continues to populate O*NET with new data, so it is plausible that subsequent releases will not suffer from this limitation.
[42] Consider the following example. If an occupation has an average importance score of 6 for high exposure activities, 4 for medium exposure activities, and 1 for low exposure activities, its normalized (relative) high exposure value would be 6/(6+4+1)=0.545. We normalize this way to prevent undue influence from occupations where all activities are rated as either very high or very low importance.
[43] Our results *are* sensitive to whether we normalize high-, medium-, and low- exposure tasks. Spearman rank correlation coefficients cannot reject the null hypothesis that the set of occupations that are highly exposed are independent (p=.29). We prefer the normalized results because 1) Kochhar (2023) performs this normalization, 2) without normalization, the highly exposed measure does not capture which tasks have the most *relative* importance

A.2 contains a list the top 50 most highly exposed occupations, which are defined based on the relative importance of their high-exposure work activities.

Occupational codes in the ACS are not the same as codes used in O*NET. To crosswalk O*NET classifications to ACS codes we take the intermediate step of matching O*NET classifications to National Employment Matrix (NEM) codes.[44] We then aggregate O*NET codes to NEM codes, leaving 750 occupations. From there, we match NEM codes to occupational codes used in the ACS. This generally required aggregating down from many NEM codes to relatively fewer ACS occupation codes. For three occupations, there are multiple ACS codes for a single NEM code. We avoid this problem by using the ACS code and reclassifying the ACS occupation as an aggregated occupation.[45] Finally we match these data to ACS microdata for the 5-year 2022 ACS, leaving us with 494 occupations for use in our analysis. We keep only employed workers. This is because we cannot observe someone's occupation if they are not employed. The merge between ACS and O*NET data captures approximately 95 percent of persons with occupational codes in ACS.

When aggregating from O*NET to NEM to ACS, we take the mean of the relative importance of high-, medium-, and low-exposure activities to obtain the relative importance metrics for each aggregated occupation. This approach implicitly assigns equal weight to each disaggregated occupation, which may not be accurate if certain disaggregated occupations have substantially different employment levels. This may bias our estimates of relative importance of high-exposure activities if exposure activities tend to be quite different. That said, 1) we know of no empirical way to estimate employment shares within the disaggregated occupations; 2) we generally did not observe large differences in relative importance of high AI exposure between the sub-occupations, suggesting whatever biases or measurement error caused by this approach are likely small; and 3) since we aggregate fewer occupations than Kochhar (2023), our approach is at least as good as their study, which relied in matching to relatively fewer CPS codes.

Kochhar (2023) defines "highly exposed" occupations as those whose relative importance of high exposure work activities is in the top quartile. Using ACS data, we instead classify those who are highly exposed to AI as the quarter of employed workers in the most highly exposed occupations (based on that occupation's relative importance of high-exposure activities) and define highly exposed occupations as the subset of occupations held by these workers. Using this definition there are 163 highly exposed occupations.

In our geographic analysis we then collapse the data to either the state level or the state-PUMA level, using personal weights in either case, and define geographic exposure based on the share of workers living in an area that are highly exposed to AI.

to an occupation, potentially leading to biases arising from some occupations reporting almost all activities are highly important or not very important.

[44] Download at: nem-onet-to-soc-crosswalk.xlsx (live.com)

[45] We applied this procedure to NEM codes "31-1120", "21-1018", and "13-1020."

Table A.1 Assignment of AI Exposure Rating by Work Activity

High Exposure Task	Medium Exposure Task	Low Exposure Task
1. Getting Information	1. Identifying Objects, Actions, and Events	1. Performing General Physical Activities
2. Monitoring Processes, Materials, or Surroundings	2. Inspecting Equipment, Structures, or Materials	2. Handling and Moving Objects
3. Processing Information	3. Estimating the Quantifiable Characteristics of Products, Events, or Information	3. Repairing and Maintaining Mechanical Equipment
4. Evaluating Information to Determine Compliance with Standards	4. Judging the Qualities of Objects, Services, or People	4. Repairing and Maintaining Electronic Equipment
5. Analyzing Data or Information	5. Updating and Using Relevant Knowledge	5. Establishing and Maintaining Interpersonal Relationships
6. Making Decisions and Solving Problems	6. Developing Objectives and Strategies	6. Assisting and Caring for Others
7. Thinking Creatively	7. Organizing, Planning, and Prioritizing Work	7. Resolving Conflicts and Negotiating with Others
8. Scheduling Work and Activities	8. Interpreting the Meaning of Information for Others	8. Developing and Building Teams
9. Controlling Machines and Processes	9. Communicating with Supervisors, Peers, or Subordinates	9. Coaching and Developing Others
10. Operating Vehicles, Mechanized Devices, or Equipment	10. Communicating with People Outside the Organization	
11. Working with Computers	11. Selling or Influencing Others	
12. Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment	12. Coordinating the Work and Activities of Others	
13. Documenting/Recording Information	13. Training and Teaching Others	
14. Performing for or Working Directly with the Public	14. Guiding, Directing, and Motivating Subordinates	
15. Performing Administrative Activities	15. Providing Consultation and Advice to Others	
16. Monitoring and Controlling Resources	16. Staffing Organizational Units	

Source: Kochhar (2023), O*NET.

Table A.2 Top 50 Most Highly Exposed Occupations Based on Relative Importance of High-Exposure Work Activities

Rank	Occupational Title (ACS)	Relative Importance of Work Activity by AI Exposure Classification		
		High	Medium	Low
1	Judicial law clerks	0.404	0.252	0.344
2	Proofreaders and copy markers	0.399	0.273	0.327
3	Eligibility interviewers, government programs	0.397	0.270	0.333
4	Title examiners, abstractors, and searchers	0.392	0.264	0.344
5	Architectural and civil drafters	0.391	0.251	0.358
6	Medical transcriptionists	0.390	0.289	0.321
7	Production, planning, and expediting clerks	0.388	0.262	0.350
8	Other drafters	0.388	0.267	0.346
9	Commercial and industrial designers	0.388	0.259	0.353
10	Billing and posting clerks	0.386	0.277	0.337
11	Switchboard operators, including answering service	0.386	0.289	0.325
12	Court reporters and simultaneous captioners	0.386	0.274	0.340
13	Tax preparers	0.385	0.272	0.343
14	Private detectives and investigators	0.385	0.266	0.349
15	Bookkeeping, accounting, and auditing clerks	0.385	0.274	0.341
16	Biological technicians	0.384	0.283	0.333
17	Paralegals and legal assistants	0.384	0.272	0.344
18	Payroll and timekeeping clerks	0.382	0.281	0.336
19	Property appraisers and assessors	0.382	0.264	0.354
20	Lawyers, and judges, magistrates, and other judicial workers	0.380	0.265	0.355
21	Loan interviewers and clerks	0.380	0.279	0.341
22	Surveyors, cartographers, and photogrammetrists	0.379	0.280	0.341
23	Court, municipal, and license clerks	0.379	0.291	0.331
24	Surveying and mapping technicians	0.378	0.286	0.336
25	Insurance claims and policy processing clerks	0.377	0.278	0.345
26	Legal secretaries and administrative assistants	0.377	0.294	0.329
27	Data entry keyers	0.377	0.279	0.344
28	Office clerks, general	0.377	0.292	0.331
29	Information security analysts	0.377	0.261	0.363
30	Aerospace engineers	0.376	0.256	0.368
31	Secretaries and administrative assistants, except legal, medical, and executive	0.376	0.297	0.327
32	Credit analysts	0.376	0.256	0.369
33	Electrical and electronics engineers	0.376	0.277	0.347
34	Budget analysts	0.375	0.258	0.367
35	Physical scientists, all other	0.375	0.256	0.369

36	Chemical engineers	0.375	0.258	0.368
37	Economists	0.374	0.229	0.398
38	Other information and records clerks	0.373	0.273	0.354
39	Aircraft pilots and flight engineers	0.373	0.289	0.338
40	Web developers	0.373	0.256	0.371
41	Credit counselors and loan officers	0.373	0.276	0.351
42	Other mathematical science occupations	0.372	0.250	0.377
43	Correspondence clerks and order clerks	0.372	0.286	0.342
44	Computer and information research scientists	0.371	0.255	0.374
45	Computer hardware engineers	0.371	0.267	0.362
46	Claims adjusters, appraisers, examiners, and investigators	0.371	0.276	0.353
47	Securities, commodities, and financial services sales agents	0.371	0.262	0.367
48	Couriers and messengers	0.370	0.329	0.301
49	Astronomers and physicists	0.370	0.257	0.373
50	Insurance sales agents	0.370	0.276	0.354

This table only reports the top 50 occupations based on 494 occupations for which data are available in both ONET and ACS.

APPENDIX B: Supplemental Tables and Figures

Table B.1 Share of Employment Highly Exposed to AI by States, Ranked

Rank	State Name	Highly Exposed Share	Rank	State Name	Highly Exposed Share	Rank	State Name	Highly Exposed Share
1	District Of Columbia	39.8	18	Alaska	25.3	35	Oklahoma	23.2
2	Maryland	29.5	19	Michigan	25.1	36	Montana	23.1
3	Utah	28.1	20	Delaware	25.1	37	Iowa	23.0
4	Colorado	27.6	21	New Hampshire	25.1	38	Tennessee	22.9
5	New Jersey	27.5	22	Pennsylvania	25.0	39	Vermont	22.9
6	Arizona	27.4	23	New Mexico	24.8	40	Alabama	22.8
7	Massachusetts	27.3	24	Georgia	24.6	41	Indiana	22.7
8	Virginia	27.2	25	Missouri	24.5	42	South Carolina	22.6
9	Connecticut	26.5	26	Texas	24.4	43	Nevada	22.3
10	New York	26.3	27	Idaho	24.3	44	Kentucky	22.2
11	California	26.0	28	Wisconsin	24.3	45	Louisiana	22.2
12	Washington	25.7	29	Ohio	24.2	46	South Dakota	22.1
13	Minnesota	25.7	30	Nebraska	23.9	47	West Virginia	21.3
14	Illinois	25.6	31	Kansas	23.9	48	Arkansas	20.9
15	Florida	25.5	32	Hawaii	23.8	49	North Dakota	20.7
16	Oregon	25.5	33	North Carolina	23.6	50	Wyoming	20.1
17	Rhode Island	25.4	34	Maine	23.4	51	Mississippi	19.5

Table B.2: Remote Workability of Highly Exposed Occupations

Occupation Title	Fully Remote Possible?
Medical assistants	No
Computer systems analysts	Yes
Insurance sales agents	Yes
Other engineers	Mostly Yes
Other office and administrative support workers	Yes
Computer support specialists	Yes
Computer occupations, all other	Yes
Real estate brokers and sales agents	Mostly Yes
Bookkeeping, accounting, and auditing clerks	Yes
Lawyers, and judges, magistrates, and other judicial workers	Mostly Yes
Receptionists and information clerks	No
Sales representatives, wholesale, and manufacturing	Yes
Office clerks, general	Yes
Accountants and auditors	Yes
Secretaries and administrative assistants, except legal, medical, and executive	Yes
Customer service representatives	Yes

Source: ACS (via IPUMS); Dingel and Neiman (2020); O*NET; author's calculations. Selected observations are highly exposed occupations with at least 500,000 estimated total employment. 'Mostly Yes' means an estimated 50% and 90% of jobs in the occupation can be done remotely. This occurs within occupations because of aggregation from detailed O*NET codes to less detailed ACS occupation codes.

Table B.3: Complete List of Fields by AI Exposure

Rank	Field of Study	% Highly Exposed	STEM?	Rank	Field of Study	% Highly Exposed	STEM?
1	Actuarial science	66	Yes	88	Intercultural and int'l studies	36	No
2	Pharmacy, pharma. sciences, and admin.	64	Yes	89	Ecology	36	Yes
3	Aerospace engineering	63	Yes	90	United states history	36	No
4	Architecture	61	No	91	Biochemical sciences	35	Yes
5	Civil engineering	60	Yes	92	Criminology	35	No
6	Mechanical engineering	60	Yes	93	Art history and criticism	35	No
7	Environmental engineering	59	Yes	94	Microbiology	35	Yes
8	Computer info. mgt and security	59	Yes	95	English language and literature	35	No
9	Atmospheric sciences and meteorology	59	Yes	96	Public administration	34	No
10	Architectural engineer.	58	Yes	97	Molecular biology	34	Yes
11	Electrical engineering	58	Yes	98	Cognitive science and biopsychology	34	Yes
12	Petroleum engineering	58	Yes	99	Military technologies	34	Yes
13	Accounting	58	No	100	Anthropology and archeology	34	No
14	Pre-law & legal studies	57	No	101	Agricultural economics	33	No
15	Computer and information systems	55	Yes	102	Area, ethnic, and civilization studies	33	No
16	Computer engineering	55	Yes	103	Community and public health	33	No
17	Commercial art and graphic design	55	No	104	Oceanography	33	Yes
18	Nuclear engineering	55	Yes	105	Health and medical administrative services	33	No
19	Materials science	55	Yes	106	Ling. and comp. lang. and lit.	33	No
20	Geosciences	54	Yes	107	Criminal justice and fire protection	32	No
21	Information sciences	54	Yes	108	Other foreign languages	32	No
22	Computer Programming and data processing	54	Yes	109	Sociology	32	No
23	Computer science	54	Yes	110	Physical sciences	32	Yes
24	Chemical engineering	53	Yes	111	Philosophy and religious stud.	32	No
25	Transportation sciences and technologies	53	No	112	Plant science and agronomy	31	Yes
26	Comm. disorders sciences and services	53	No	113	Drama and theater arts	31	No
27	Electrical engineering technology	52	Yes	114	Liberal arts	31	No
28	Statistics and decision science	51	Yes	115	Neuroscience	31	Yes
29	Materials engineering and materials science	51	Yes	116	Humanities	30	No
30	Mechanical engineering related technologies	51	Yes	117	Multi-disciplinary or general science	29	Yes

31	Geological and geophysical engineer.	51	Yes
32	Engineering mechanics, physics, and science	51	Yes
33	General engineering	51	Yes
34	Pharmacology	50	Yes
35	Applied mathematics	49	Yes
36	Management info. systems and statistics	49	No
37	Geology and earth science	49	Yes
38	Math and comp. science	49	Yes
39	Mining and mineral engineering	48	Yes
40	Biomedical engineering	48	Yes
41	Computer networking and telecommunications	48	Yes
42	Physics	47	Yes
43	Political science and government	47	No
44	Finance	46	No
45	Soil science	45	Yes
46	Naval architecture and marine engineering	45	Yes
47	Geography	45	No
48	Journalism	45	No
49	Miscellaneous engineering	45	Yes
50	Communication technologies	44	No
51	Business economics	44	No
52	Industrial and manufacturing engineering	44	Yes
53	Metallurgical engineering	44	Yes
54	Miscellaneous Biology	44	Yes
55	Biological engineering	44	Yes
56	Engineering technologies	43	Yes
57	Astronomy and astrophysics	43	Yes
58	Misc. engineer. tech.	43	Yes
59	Economics	43	No
60	Environmental science	42	Yes
61	public policy	42	No

118	Miscellaneous agriculture	29	No
119	Interdisciplinary social sciences	29	No
120	General social sciences	29	No
121	Agriculture production and management	29	No
122	Common foreign language studies (e.g., French)	28	No
123	Human resources and personnel management	28	No
124	Biology	28	Yes
125	Social psychology	27	Yes
126	Industrial and organizational psychology	26	No
127	Psychology	26	No
128	Hospitality management	26	No
129	Electrical and mechanic repairs and tech.	26	No
130	General agriculture	26	No
131	Miscellaneous psychology	26	Yes
132	Visual and performing arts	26	No
133	Interdiscip. and multi-discip. studies (general)	25	No
134	Construction services	25	No
135	Human services and community organization	25	No
136	Zoology	24	Yes
137	Family and consumer sciences	24	No
138	Animal sciences	24	Yes
139	Miscellaneous education	23	No
140	General medical and health services	23	No
141	Music	22	No
142	Medical technologies technicians	22	No
143	Library science	22	No
144	Social work	22	No
145	Physiology	22	Yes
146	Physical fitness, parks, recreation, and leisure	22	No
147	N/A	20	
148	Nutrition sciences	19	Yes

62	International relations	42	No	149	Theology and religious vocations	19	No
63	Mass media	41	No	150	Health and medical preparatory programs	19	No
64	Natural resources management	41	Yes	151	Clinical psychology	19	No
65	Miscellaneous fine arts	41	No	152	Miscellaneous health medical professions	18	No
66	Advert. & pub. relations	41	No	153	Secondary teacher education	17	No
67	Forestry	40	Yes	154	Social science or history teacher education	16	No
68	Miscellaneous business and medical admin.	40	No	155	Science and computer teacher education	16	No
69	Genetics	40	Yes	156	Counseling psychology	16	No
70	Chemistry	40	Yes	157	Physical and health education teaching	15	No
71	Food science	39	Yes	158	Cosmetology services and culinary arts	15	No
72	Composition and speech	39	No	159	Medical assisting services	15	No
73	Industrial prod. tech.	39	Yes	160	Art and music education	14	No
74	International business	39	No	161	Language and drama education	14	No
75	operations, logistics and e-commerce	39	No	162	Mathematics teacher education	14	No
76	Marketing and marketing research	39	No	163	Nuclear, industrial radiology, and biological tech.	13	Yes
77	Mathematics	38	Yes	164	General education	13	No
78	Business management and administration	38	No	165	Educational psychology	12	No
79	General business	38	No	166	Elementary education	12	No
80	Botany	38	Yes	167	Early childhood education	12	No
81	Fine arts	37	No	168	Treatment therapy professions	11	No
82	Communications	37	No	169	School student counseling	10	No
83	Film, video, and photographic arts	37	No	170	Teacher education: multiple levels	10	No
84	Miscellaneous social sciences	37	No	171	Special needs education	9	No
85	Engineering and industrial management	36	Yes	172	Educational administration and supervision	9	No
86	History	36	No	173	Nursing	6	No
87	Studio arts	36	No				

Source: ACS, O*NET. Sample only includes employed workers. STEM= Science, Technology, Engineering, or Mathematics. STEM or non-STEM designations based on the Department of Homeland Security's STEM Designated Degree Program List.

Table B.4: Fields of Study by Share in Highly AI Exposed Occupations; Broad Categories of Fields of Study

Field	% in Highly Exposed Occupations
Architecture	61.4
Law	57.3
Engineering	55.6
Computer and information sciences	54.3
Transportation sciences and technologies	53.2
Engineering technologies	44.7
Communication technologies	44.1
Business	42.3
Environment and natural resources	41.6
Social sciences	40.6
Communications	39.7
Mathematics and statistics	39.6
Physical sciences	39.4
Fine arts	37.8
History	36.0
English language, literature, and composition	34.9
Military technologies	33.7
Area, ethnic, and civilization studies	33.1
Criminal justice and fire protection	32.5
Philosophy and religious studies	31.5
Liberal arts and humanities	30.7
Linguistics and foreign languages	29.9
Biology and life sciences	29.5
Agriculture	28.5
Interdisciplinary and multi-disciplinary studies (general)	28.3
Electrical and mechanic repairs and technologies	25.9
Psychology	25.7
Public affairs, policy, and social work	25.2
Construction services	25.0
Family and consumer sciences	24.4
Library science	21.9
Physical fitness, parks, recreation, and leisure	21.6
Theology and religious vocations	19.3
Medical and health sciences and services	17.0
Cosmetology services and culinary arts	14.8
Nuclear, industrial radiology, and biological technologies	13.4
Education administration and teaching	13.0

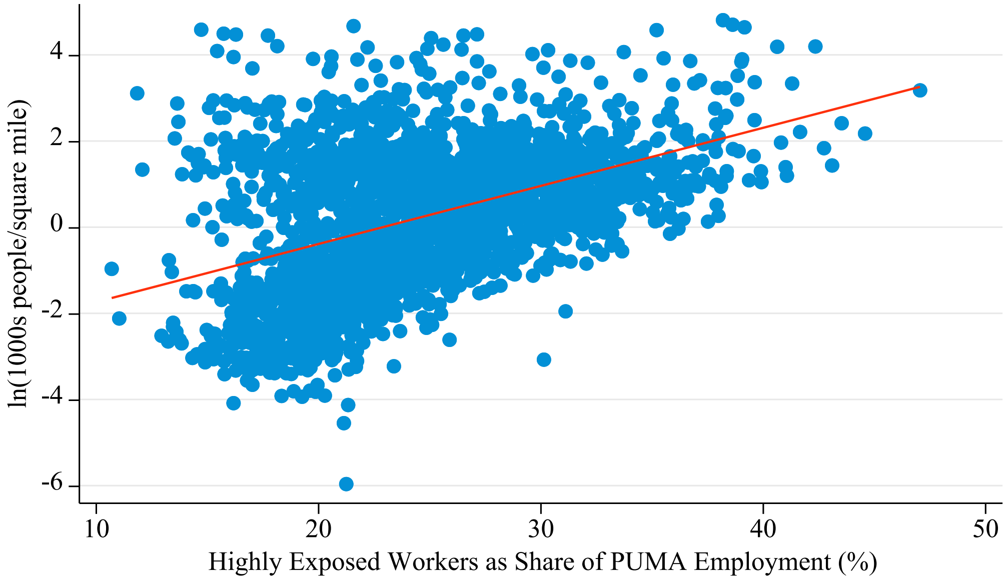
Source: ACS (via IPUMS); O*NET.

Table B.5: Racial Composition of College Graduates in Most Highly AI Exposed Majors

Field of Study / Major	% Exposed	Hispanic	Black	Asian or Pacific Islander	White, Non-Hispanic
Actuarial science	66.8	5.3	5.4	16.6	70.7
Pharmacy, pharma. sciences, and administration	65.1	5.4	7.0	22.8	62.8
Aerospace engineering	63.9	8.4	4.3	12.5	71.3
Civil engineering	60.8	11.0	4.2	15.2	66.7
Architecture	60.6	14.2	5.2	11.7	65.9
Mechanical engineering	60.5	8.9	3.6	17.4	67.3
Environmental engineering	59.8	11.0	3.3	14.9	67.4
Computer information management and security	59.3	11.5	14.5	8.4	62.3
Atmospheric sciences and meteorology	58.9	5.8	3.6	8.7	78.0
Electrical engineering	58.7	8.8	5.5	29.6	53.4
Petroleum engineering	58.4	15.1	6.7	7.3	67.1
Architectural engineering	58.3	5.6	7.4	10.1	74.7
Accounting	57.4	10.0	9.0	11.6	67.2
Pre-law and legal studies	57.4	11.5	14.4	5.5	65.1
Computer and information systems	55.8	9.6	14.1	18.2	54.6
Computer engineering	55.6	12.9	6.3	33.4	44.7
Geosciences	55.1	9.9	3.1	19.5	65.4
Nuclear engineering	55.0	6.1	2.9	9.5	78.6
Materials science	54.9	4.3	2.7	35.2	54.0
Information sciences	54.8	9.0	13.4	16.3	58.3
Commercial art and graphic design	54.4	11.2	6.9	9.8	69.0
Computer science	54.2	8.4	8.9	24.5	54.8
Computer programming and data processing	53.9	11.8	11.8	13.0	60.0
Transportation sciences and technologies	53.6	9.4	6.1	4.9	76.4
Chemical engineering	53.6	9.4	5.2	20.7	62.3
Communication disorders sciences and services	53.0	8.8	6.8	5.2	77.1
Electrical engineering technology	52.2	8.9	8.7	31.1	48.9
Mechanical engineering related technologies	52.1	7.7	7.0	8.1	75.1
Statistics and decision science	51.7	5.5	7.5	34.1	49.5
Pharmacology	51.7	8.9	8.7	27.5	52.0
Materials engineering and materials science	51.6	5.8	2.9	21.0	67.2
General engineering	51.4	12.5	8.2	17.9	58.4
Engineering mechanics, physics, and science	51.3	11.2	3.7	13.5	68.9
Geological and geophysical engineering	50.4	8.7	5.0	6.1	78.0

Source: ACS (via IPUMS); O*NET. Sample includes employed workers with positive earnings. Cells represent shares of the college-educated workforce in each field by race (e.g., 10.0 percent of accounting graduates in the sample are Hispanic). Rows do not sum to 100 percent because not all race/ethnic groups shown. Bold values indicate that group's share in that field is larger than that group's share of employed college graduates in our overall sample.

Figure B.1. Correlation Between Log Density and High Exposure, by PUMA

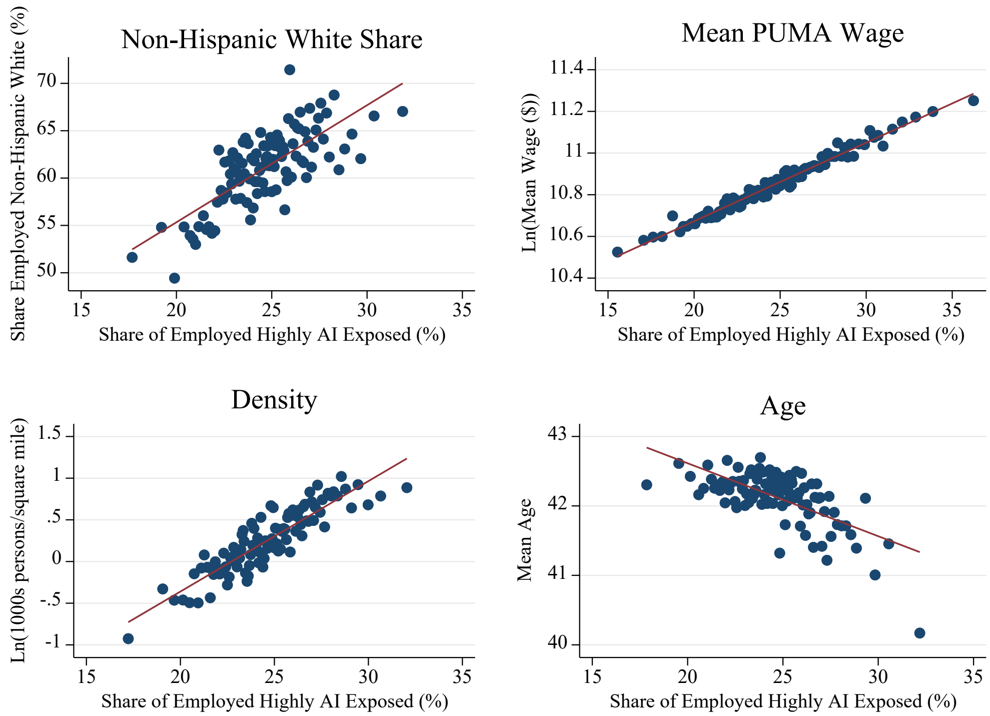


Notes: Red line is a line of best fit. Data from BLS, ACS, and Kochhar (2023). PUMA = Public Use Micro Area. See text for details.

Figure B.2. Correlation Between Density and High AI Exposure, by PUMA

Notes: Red line is a line of best fit. Data from BLS, ACS, and Kochhar (2023). PUMA= Public Use Micro Area. See text for details.

Figure B.3. Residualized Binned Scatterplots



Source: O*NET, ACS (2021 5-year), and Kochhar (2023). Each scatterplot is residualized by state fixed effects and each other variable shown in the graph (e.g., estimates in the graph labeled “Non-Hispanic White Share” include controls for mean PUMA wage, density, and age). See footnote to Figure 3 for details about binned scatterplots.

APPENDIX C: Concentration of Fields of Study Within Occupations

Our main focus in our analysis by education is on the flow of majors into occupations – i.e., do business majors tend to flow into highly AI exposed occupations or not? In our conceptual framework we consider how demand shocks for different skills, as a result of developments in AI, may affect demand for workers with BAs in certain fields. That said, the reverse may also matter. That is, AI may result in changes in fields of study. In this way, an *occupation* may be impacted by an AI-inducted shock to fields of study. For example, if developments in AI make it easier for people to learn new languages, perhaps French or Spanish majors could graduate at an accelerated pace. Occupations that draw heavily from such majors may then be exposed downstream to this shock.

In most occupations, field of study (among those with a bachelor's degree) is not highly concentrated (See Figure C.1). For example, the top five fields of study for budget analysts (business administration and management, accounting, finance, general business, and economics) account for only 55 percent of college graduates working as a budget analyst. Other fields, such as psychology, history, mathematics, account for nearly half of the college graduates working as budget analysts. However, some occupations draw from a very concentrated set of degrees of study. For example, among registered nurses, 73 percent studied nursing as their primary field of study in college, with the second most common field (biology) accounting for less than 3 percent.

Of the 494 occupations we consider[46], 30 have HHIs of 2,000 or greater (highly concentrated) and 23 have HHIs between 1500-2000 (moderately concentrated). That is, for these occupations, a very large share of workers with a bachelor's degree studied a very small subset of fields. Just over half (27) of these concentrated occupations are occupations that are highly exposed to AI.

Despite a significantly higher share of college graduates in occupations highly exposed to AI (Figure 2), the concentration of fields of study among college graduates is not substantially different for highly exposed occupations than less highly exposed occupations (Figure C.2, Table C.1).

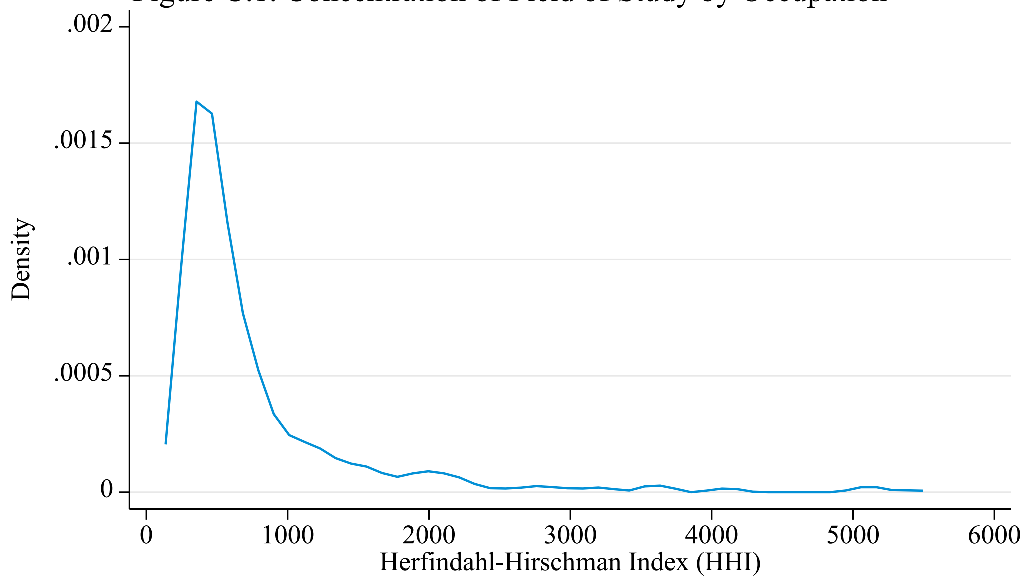
[46] HHI scores based on 172 fields of study for which we have data (excludes "N/A", which indicates no field of study, i.e., no bachelor's degree).

Table C.1. Occupations with High Concentration of Field of Study

Occupation	HHI of Field of Study	Highly Exposed to AI?
Registered nurses	5410	No
Audiologists	5159	No
Nurse anesthetists	5090	No
Nurse practitioners, and nurse midwives	5085	No
Architects, except landscape and naval	4130	Yes
Landscape architects	4077	Yes
School psychologists	3648	No
Astronomers and physicists	3620	Yes
Speech-language pathologists	3618	Yes
Electrical and electronics engineers	3504	Yes
Geoscientists and hydrologists, except geographers	3239	Yes
Chemical engineers	3218	Yes
Atmospheric and space scientists	3068	Yes
Clinical and counseling psychologists	2909	No
Fashion designers	2842	No
Other psychologists	2781	No
Mechanical engineers	2682	Yes
Accountants and auditors	2597	Yes
Recreational therapists	2422	No
Pharmacists	2313	Yes
First-line supervisors of police and detectives	2276	No
First-line supervisors of correctional officers	2233	No
Chemists and materials scientists	2186	Yes
Musicians and singers	2171	No
Biological technicians	2149	Yes
Boilermakers	2121	No
Optometrists	2079	No
Music directors and composers	2076	No
Economists	2068	Yes
Probation officers and correctional treatment specialists	2065	Yes

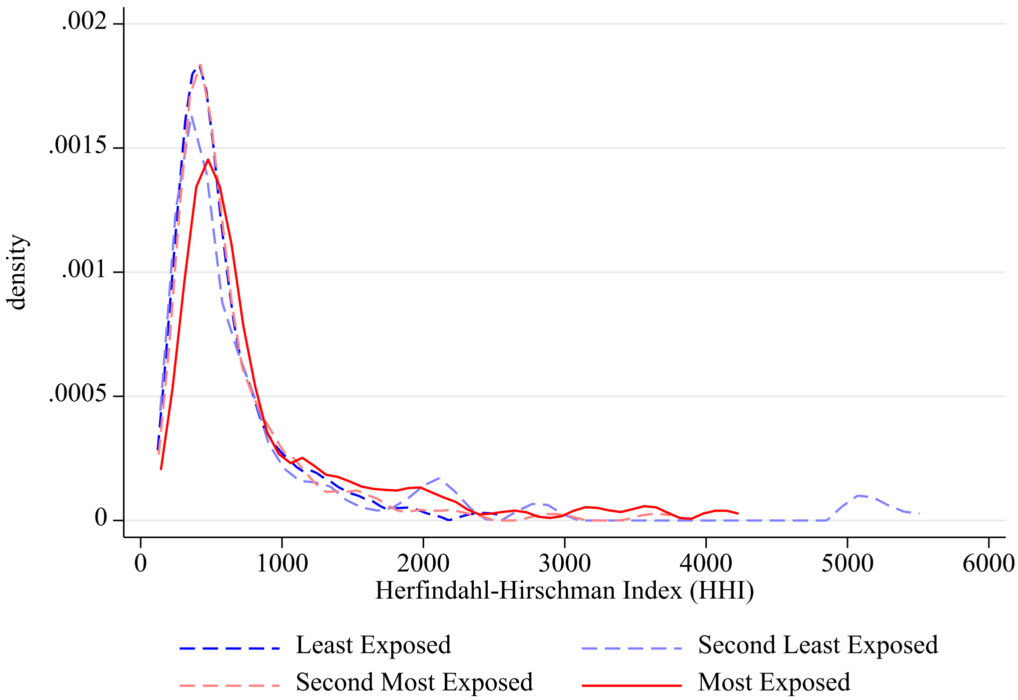
Source: ACS, O*NET, author's calculations. HHI=Herfindahl-Hirschman Index.

Figure C.1. Concentration of Field of Study by Occupation



Source: ACS. Sample only includes workers with known occupations that could be matched to O*NET data. Density estimates constructed using Epanechnikov kernel.

Figure C.2. Concentration of Field of Study by Occupation and AI Exposure



Source: ACS, O*NET. Sample only includes workers with known occupations that could be matched to O*NET data. Density estimates constructed using Epanechnikov kernel (bandwidth=100 for all).