How Adaptable Are American Workers to AI-Induced Job Displacement?

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Abstract

We construct an occupation-level adaptive capacity index that measures a set of worker characteristics relevant for navigating job transitions if displaced, covering 356 occupations that represent 95.9% of the U.S. workforce. We find that AI exposure and adaptive capacity are positively correlated: many occupations highly exposed to AI contain workers with relatively strong means to manage a job transition. Of the 37.1 million workers in the top quartile of AI exposure, 26.5 million are in occupations that also have above-median adaptive capacity, leaving them comparatively well-equipped to handle job transitions if displacement occurs. At the same time, 6.1 million workers (4.2% of the workforce in our sample) work in occupations that are both highly exposed and where workers have low expected adaptive capacity. These workers are concentrated in clerical and administrative roles. Importantly, AI exposure reflects potential changes to work tasks, not inevitable displacement; only some of the changes brought on by AI will result in job loss. By distinguishing between highly exposed workers with relatively strong means to adjust and those with limited adaptive capacity, our analysis shows that exposure measures alone can obscure both areas of resilience to technological change and concentrated pockets of elevated vulnerability if displacement were to occur.

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1 Introduction

A robust body of research estimates the degree of AI exposure across occupations in the U.S. labor market (Brynjolfsson et al. 2018; Webb 2020; Felten et al. 2023; Eloundou et al. 2024; Hampole et al. 2025). Although definitions vary, a work task is generally considered "exposed" when an AI system possesses capabilities relevant to performing it. Prior research has taken task-level AI exposure measures and aggregated them up to the occupation level, estimating the share of a job's tasks exposed to AI. Exposure measures do not offer a prediction about which jobs will be displaced. Instead, these measures indicate potential for labor market change that can take many forms for workers depending on numerous other non-technical factors (Acemoglu and Restrepo 2019; Manning 2024; Autor and Thompson 2025). At best, exposure may often be a necessary but not sufficient condition for AI-driven displacement.

While exposure measures help identify where labor market change could occur, they do not capture how well-positioned workers are to adapt if disruption leads to displacement. Despite the fact that labor-saving technologies have generated many long-run benefits for workers and consumers (Autor 2015; Mokyr et al. 2015), involuntary job loss does impose substantial costs on displaced workers, affecting earnings, health, and even mortality (Jacobson et al. 1993; Gallo et al. 2006; Sullivan and Von Wachter 2009). Market failures, including liquidity constraints, labor market frictions, and coordination failures in reskilling, amplify these displacement costs (Chetty 2008; Beraja and Zorzi 2025; Adão et al. 2024). These costs are not borne equally across affected workers: liquid financial resources, the transferability of workers' skills across jobs, geographic concentration of employment opportunities, and age can all shape how well individuals manage job transitions, for example (Chetty 2008; Nawakitphaitoon and Ormiston 2016; Bleakley and Lin 2012; Gathmann et al. 2020; Eggenberger et al. 2022; Neffke et al. 2024; Athey et al. 2024).

In this paper, we extend the literature on AI exposure by introducing an occupation-level adaptive capacity index that captures a set of worker characteristics relevant for navigating job transitions if displaced. We understand adaptive capacity as the ability of workers to successfully navigate job transitions and minimize welfare costs if they suffer job displacement. Specifically, we construct an adaptive capacity index that incorporates estimates of net liquid wealth, skill transferability, geographic density, and age for workers in 356 occupations covering 95.9% of the

U.S. workforce. We focus particularly on factors that may influence displaced workers' ability to find new jobs and their earnings after reemployment, even though only a portion of all AI exposure may eventually lead to displacement. This approach allows us to distinguish between highly exposed workers with relatively strong means to adjust if displaced and those with limited adaptive capacity who may face greater welfare costs if displacement occurs. We define an occupation as "vulnerable" if it combines high AI exposure with low adaptive capacity. These are jobs where workers face a higher risk of costly displacement *if* exposure to AI leads to job loss. Importantly, "vulnerable" does not mean workers in these occupations will inevitably be displaced—predicting displacement is beyond the scope of this paper.

Our findings establish four key patterns: (1) AI exposure and adaptive capacity are positively correlated ($r = 0.502$); (2) approximately 4.2% of the workforce are in occupations that face high exposure and low adaptive capacity; (3) these workers are concentrated in clerical and administrative occupations; and (4) high AI exposure bifurcates into professional roles (high adaptive capacity) versus clerical positions (low adaptive capacity). This means that many of the most exposed occupations have workers with relatively strong means to adjust after displacement. For example, of the 37.1 million workers in the top quartile of AI exposure, 26.5 million also have above-median adaptive capacity, leaving them relatively well-placed to navigate job transitions. At the same time, 6.1 million workers (4.2% of the workforce in our sample) are both highly exposed and in the bottom quartile of adaptive capacity. These workers are concentrated in clerical, administrative support, and assistance roles, not the managerial, professional and technical occupations that, while similarly exposed, tend to have higher savings and more transferable skills for adapting to potential displacement. Geographically, high-exposure/low-capacity occupations are concentrated in college towns and state capitals in the Mountain West and Midwest, though large cities contain the greatest absolute numbers of such workers due to their size. These patterns remain largely robust across alternative specifications of the adaptive capacity index, as we discuss in the Online Appendix.

2 Literature Review

This study sits at the intersection of two research streams: (1) work that measures and forecasts AI's impact on labor markets, and (2) research examining how workers recover from job displacement.

By bridging these literatures, we move beyond identifying which jobs face potential AI exposure to understanding which workers might face the greatest or least adjustment costs if disruption leads to displacement.

2.1 AI Exposure and Labor Market Impacts

The task-based framework, introduced by Autor et al. (2003) and further developed by Acemoglu and Autor (2011), provides the main theoretical foundation for understanding AI's impact on labor markets. This framework conceptualizes jobs as bundles of tasks that can be allocated between humans and machines. When technology advances, it creates three primary effects: a displacement effect where AI directly substitutes for human labor in certain tasks; a scale (productivity) effect where AI increases efficiency and potentially expands output; and a reinstatement effect where new technologies create new tasks in which humans have comparative advantage. As Acemoglu and Restrepo (2019) emphasizes, the net impact on labor demand depends on the balance of these forces and on factors such as the elasticity of product demand. This framework therefore explains why AI can have complex and uneven effects across occupations and sectors.

A growing body of research has mapped occupational tasks to AI capabilities to measure potential disruption. Brynjolfsson et al. (2018) used O∗NET task data to develop a "Suitability for Machine Learning" measure, finding that while most occupations contain some automatable tasks, few jobs could be completely automated. Webb (2020) analyzed overlap between patent text and occupational descriptions, showing that higher-wage occupations are disproportionately exposed to AI technologies. Felten et al. (2023) linked AI applications to human abilities and then to occupations using O∗NET data. Eloundou et al. (2024) created a rubric to evaluate the share of O∗NET tasks for which GPT-4–class LLMs could potentially double worker productivity. More recently, Hampole et al. (2025) developed firm-occupation-level measures of AI exposure using natural language processing to link AI applications from resume data to occupational tasks, finding both direct substitution effects and productivity spillovers across tasks within occupations. Across these studies, higher-income occupations requiring post-secondary education consistently show the highest exposure to AI.

Studies tracking actual AI adoption patterns largely confirm these exposure predictions. In a review of recent surveys, Crane et al. (2025) documented that 20–40% of employees now incorporate

AI in their work, with adoption rates highest among programmers (84–97%) and other technical professionals, while significantly lower in public service roles (22%). Pew Research Center (2024) found that ChatGPT use among U.S. workers rose from 8% in March 2023 to 20% in February 2024. One U.S. study found LLM adoption among workers increased from 30% in December 2024 to 38% by December 2025 (Hartley et al. 2025). The correlation between predicted occupational exposure (Eloundou et al. 2024) and observed adoption is estimated at roughly 0.67 (Bick et al. 2024), suggesting that exposure may be a relatively strong predictor of actual usage. Evidence from Anthropic's Economic Index finds a positive correlation between predicted and observed measures, but with discrepancies in areas such as healthcare (Handa et al. 2025).

The high exposure of highly educated, high-income workers to AI might lead to hasty conclusions that these workers will bear the greatest burden from technological disruption. This overlooks that exposure can have very different impacts on worker outcomes based on a variety of non-technical factors. Exposure studies identify where tasks may be affected but do not distinguish between complementary effects (enhancing productivity and boosting labor demand) and substitutive effects (displacing workers). Nor can they predict the welfare consequences of potential change for individuals. The costs of job transitions, for example, will vary widely, depending on workers' financial resources, skills, age, and other characteristics that determine their ability to find new employment.

2.2 Factors that Influence Worker Adaptive Capacity to AI-driven Labor Market Transitions

Displaced workers can face immediate earnings losses, with scars that can persist for over a decade (Jacobson et al. 1993; Couch and Placzek 2010; Wachter et al. 2011). Longitudinal evidence shows persistent income instability lasting 15–20 years and even elevated mortality risk following displacement (Sullivan and Von Wachter 2009). However, the negative impacts of displacement are not borne evenly across all affected workers. These costs are typically greatest among workers with lower skills (Acemoglu and Autor 2011; Autor et al. 2013), limited savings (Chetty 2008; Roll and Despard 2024), and those at the extremes of the age distribution (Couch and Placzek 2010; Farber 2017).

To estimate worker adaptive capacity across U.S. occupations, we build a composite index combining four dimensions emphasized in this literature: net liquid wealth, skill transferability, geographic density, and age. These factors shape displacement costs through different mechanisms—skill transferability and age primarily determine the loss of human capital specificity, while geographic density enables better job matching and liquid wealth provides consumption smoothing with contested evidence on improving downstream job matches. These factors were chosen based on empirical support and data availability. The index is not intended to capture every possible factor influencing adaptive capacity. Other factors such as union representation, routine-task intensity, and income may also play important roles. These are discussed in the Online Appendix.

2.2.1 Liquid Financial Resources

When workers lose their jobs, those with greater savings can weather income shocks more effectively. Chetty (2008) shows that individuals with greater liquid savings are less financially distressed after job loss and can afford longer job searches. This longer search duration is welfare-improving because it corrects credit and insurance market failures—workers with liquidity can search longer rather than accepting the first available offer. Conversely, people with low liquid wealth are more constrained in their job search decisions (Beraja and Zorzi 2025). Andersen et al. (2023) find that Danish households reduce spending by 30% of their income loss following job displacement, with liquid balances accounting for 50% of self-insurance.

Beyond consumption smoothing, liquid resources may also affect subsequent job outcomes, though evidence here is more limited. Much of the debate centers on lump-sum severance payments versus extended unemployment insurance duration. Most studies find positive but small and often statistically insignificant impacts on wages. Card et al. (2007) find that severance payments worth two months of earnings allow longer search but produce no economically significant wage gains. Evidence on UI duration extensions is mixed: Nekoei and Weber (2017) find a modest positive effect in Austria, with a 9-week UI extension increasing reemployment wages by 0.5%, while Schmieder et al. (2016) find negative effects in Germany. More consistent evidence emerges for job security outcomes. Figueiredo et al. (2024) find that displacement decreases permanent employment probability by 19% within a year and 12% after five years, but workers receiving lump-sum transfers experience significantly smaller negative shocks, with effects twice as large for liquidity-constrained workers.

Liquid wealth also provides broader protection during downturns. Caratelli (2024) documents how wealthier individuals experience less substantial earnings declines during recessions, with workers below median wealth facing 10% drops in real labor earnings following the Great Recession. During COVID, Roll and Despard (2024) found that greater liquid assets lessened the probability of experiencing financial distress and moderated the effects of job loss. Gallo et al. (2006) found that older workers with below-median net worth experienced persistent depressive symptoms following involuntary job loss.

Despite limited evidence that liquidity improves reemployment wages, liquid financial resources during income disruption represent a key dimension of adaptive capacity through consumption smoothing and job security. Holding other factors constant, workers with different financial reserves are likely to experience markedly different welfare costs if displaced.

2.2.2 Age

Age significantly influences job displacement costs, primarily through the loss of occupation-specific human capital and reduced flexibility in reallocation. Recent evidence from Athey et al. (2024) identifies age as a primary predictor of displacement effects. Kogan et al. (2023) find that labor-augmenting technologies have essentially zero impact on younger workers but significant negative effects on older workers, with a 1.7 percentage point difference in earnings impacts. Gathmann et al. (2020) show that workers aged 51–65 experience persistent employment losses of 3.4 percentage points four years after mass layoffs, while workers under 50 experience virtually no losses due to greater geographic mobility. In the U.S., Farber (2017) finds that workers aged 55–64 are 16 percentage points less likely to be reemployed than those 35–44.

Older workers struggle more with displacement partly because of reduced flexibility in retraining, relocation, and occupational switching. Brzozowski and Crossley (2010) find that older job losers were less likely to retrain, relocate, or switch occupations. Couch and Placzek (2010) quantify these differences, showing older workers experience more than twice the earnings losses of younger workers. Davis and Wachter (2011) find that displacement causes greater long-term earnings losses for workers with higher tenure, who tend to be older, with losses persisting up to 20 years. Gallo et al. (2006) demonstrated more severe impacts on both physical and mental health among displaced older workers.

The literature on younger workers presents more mixed findings. Kletzer and Fairlie (2003) found young displaced men experience initial earnings losses of 18.3% declining to 9.1% after five years, while the literature they review documents persistent losses of 10-18% for older workers. Gregory and Jukes (2001) note that younger workers are less scarred than prime-age workers, though research on graduating during recessions shows new labor market entrants can experience persistent earnings penalties (Kahn 2010; Oreopoulos et al. 2012). Recent evidence from Bartal et al. (2025) helps reconcile these findings by documenting a U-shaped pattern in displacement costs across age groups. In addition, when considering the net present value of career earnings, even modest wage losses or decelerated wage growth early in a career can compound substantially over time, potentially making younger workers' displacement costs larger than cross-sectional estimates suggest. However, given the more established literature on older worker challenges, our baseline adaptive capacity index uses the fraction aged 55 or older as a contributing factor, with alternative specifications including the percentage of workers under 25.

2.2.3 Geographic Density

Where a worker lives can significantly impact their displacement experience. Frank et al. (2018) found that cities with more diversified economies and shorter skill distances between occupations provide better opportunities for job-seekers. Bleakley and Lin (2012) find that thick markets reduce occupational switching: for involuntarily displaced workers from plant closings, a one-log increase in density decreases detailed occupation switching probability by 3.3%, helping displaced workers stay in occupations where their skills remain valuable. Moretti and Yi (2024) provide comprehensive evidence using administrative data on firm closures that larger labor markets improve reemployment outcomes, with particularly strong effects for college graduates and workers with specialized human capital. Building on this evidence, our adaptive capacity index incorporates a geographic worker density measure capturing the concentration of employment opportunities available to workers in each occupation.

Studies using plant closures and mass layoffs as exogenous displacement events reinforce this pattern. Athey et al. (2024) finds population density to be among the most important predictors of displacement effects in Sweden: workers in sparse areas suffer substantially higher earnings losses than those in dense areas, even after controlling for extensive worker and establishment characteristics. Similarly, Jacobson et al. (1993) show that displaced workers face larger earnings losses in regions with weak employment growth, which is often true of low-density rural areas relative to urban areas (Dumont 2024).

While displacement effects from manufacturing automation typically manifested through plant closures that eliminated large shares of employment in affected communities (Autor et al. 2013), AI disruption may exhibit significant geographic variation. Even as remote work becomes more prevalent, local labor market thickness continues to matter: many occupations still require physical presence, professional networks remain geographically concentrated, and workers often face mobility constraints. The consistent evidence showing that population density significantly shapes displacement outcomes suggests that geographic concentration remains an important component of adaptive capacity.

2.2.4 Skill Transferability

A worker's skill profile significantly influences their ability to adapt to disruptions, primarily by determining how much occupation-specific human capital is lost during transitions. Workers with greater skill transferability across occupations can pivot more easily when their primary occupation faces disruption. Nawakitphaitoon and Ormiston (2016) find that a 10 percentage point increase in skills transferability is associated with 1-4% smaller earnings losses following displacement. Eggenberger et al. (2018) and Eggenberger et al. (2022) demonstrate the trade-off between occupation-specific training (yielding higher returns for those who stay) and general training (enabling greater mobility when needed).

Neffke et al. (2024) showed that the direction of post-displacement occupational changes strongly affects earnings recovery—workers moving to jobs demanding more skills reach counterfactual earnings within seven years, while those transitioning to less skill-demanding occupations experience permanent earnings scarring. At the macro level, Adão et al. (2024) show that adjustment to new technologies is slower when required skills differ sharply from those widely held in the economy.

As measuring skill directly is difficult, education often serves as a proxy. The literature presents mixed findings on education's role in displacement costs. Braga (2018) demonstrates that more educated workers suffer larger wage losses after displacement—bachelor's degree holders experience 20% reductions versus 3% for high school dropouts—reflecting greater loss of firm-specific training investments. By contrast, Athey et al. (2024) find higher education associated with smaller losses. Mandemakers and Monden (2013) show higher-educated workers experience less psychological distress due to superior re-employment prospects, while Berchick et al. (2012) find education buffers depressive symptoms but higher occupational prestige increases vulnerability.

Various approaches have been employed to measure skill transferability. Shaw (1984) inferred transferability from observed occupational mobility. Ormiston (2014) constructs measures comparing similarity of O∗NET knowledge, skills, and abilities between occupations. Gathmann and Schönberg (2010) estimate "skill distances" using cosine distance between job task vectors, while Yi et al. (2017) estimate sector-specific transferability. More recent work measures cosine distance between occupational skill vectors, weighting these by relative employment shares (Eggenberger et al. 2022). Building on this literature, we measure skill transferability between occupations using O∗NET skills and work activities data for each occupation, then weigh transferability measures based on projected growth or contraction in potential destination occupations using BLS employment projections (U.S. Bureau of Labor Statistics 2025), as discussed in Section 3.

3 Methodology and Data

We combine multiple national datasets to examine the relationship between AI exposure and workers' adaptive capacity to displacement at the occupational level.

3.1 Data Sources

We draw on seven primary data sources:

1. **Survey of Income and Program Participation (SIPP) 2022–2024 Panels**: U.S. Census Bureau nationally representative surveys providing data on workers' income, savings, and demographic characteristics. We pool three years of SIPP panel data (2022, 2023, 2024) to increase sample sizes for occupation-level statistics. We use SIPP to construct occupation-level measures of median net liquid wealth for the baseline adaptive capacity index.

2. **American Community Survey (ACS) 2024**: U.S. Census Bureau microdata providing occupation-level age distributions. We use ACS to measure the fraction of workers aged 55+

in each occupation for the baseline adaptive capacity index.

3. **Occupational Employment and Wage Statistics (OEWS) 2024**: A Bureau of Labor Statistics (BLS) annual survey providing occupation-level wage and employment data used for cross-dataset weightings and harmonization.

4. **BLS Employment Projections**: Projected employment growth rates by occupation (2024-2034), used to calculate growth-weighted skill transferability.

5. **Lightcast 2023**: We obtain occupation-level employment by county and Metropolitan Statistical Area (MSA) from Lightcast to calculate the expected overall labor market density where each occupation's workers are located.

6. **O∗NET Database 30.1 (2025)**: From the Department of Labor, we use importance ratings for O∗NET Skills and Work Activities to measure skill transferability across occupations in the adaptive capacity index.

7. **AI Exposure Data**: From Eloundou et al. (2024), we use the E1+0.5E2 estimates to measure occupational exposure to LLMs.

3.2 Construction of Adaptive Capacity Measures

For an occupation to be included in the dataset, it must have (a) at least 15 unique SIPP respondents, (b) employment data from OEWS, (c) median net liquid wealth from SIPP, (d) skill importance data from O∗NET (including KNN-imputed where unavailable), (e) age data from ACS, (f) geographic density data from Lightcast, and (g) AI exposure data from Eloundou et al. (2024). This final requirement excludes residual "all other" occupation categories. Following Acemoglu and Autor (2011), we use OEWS employment weights when aggregating across occupational classifications. To combine different data sources, we map occupations from O∗NET to SOC to OEWS, or from Census to SIPP, and then map both to a Modified SIPP classification to handle inconsistencies (further details included in the Online Appendix). Our analysis includes 356 occupations meeting these data quality requirements, covering 95.9% of the U.S. workforce.

The baseline adaptive capacity index includes four components that capture workers' ability to navigate potential transitions:

- **Net Liquid Wealth:** Following Chetty (2008), net liquid wealth equals total wealth minus home, business, and vehicle equity, and minus unsecured debt. This measure captures readily accessible financial buffers for job search and consumption smoothing during displacement. We apply a log transformation: $\log(\max(W, 1))$ where W is median net liquid wealth, setting a floor at 1 to handle zero or negative values.

- **Growth-Weighted Skill Transferability:** Building on prior work measuring skill distance between occupations (Gathmann and Schönberg 2010; Eggenberger et al. 2022), we measure how easily workers could transition to other occupations based on skill similarity using O*NET Skills and Work Activities importance ratings.

  We transform each skill dimension to employment-weighted percentiles across occupations, placing all skills on a common scale. We then calculate cosine similarity between these percentile-transformed profiles to measure how closely occupation pairs match. For occupation i, transferability is:

  $$T_i = \frac{\sum_j \text{employment}_j \times \text{similarity}_{ij} \times (1 + \text{growth\_rate}_j)}{\sum_j \text{employment}_j \times (1 + \text{growth\_rate}_j)},$$

  where employment_j is current employment in occupation j, similarity_{ij} is cosine similarity between percentile-transformed skill profiles, and $(1 + \text{growth\_rate}_j)$ incorporates BLS 2024-2034 employment projections. This weights similarities by current and projected employment opportunities, giving more weight to skills transferable to growing occupations. Alternative specifications using skill diversity or different O*NET dimensions are available in the Online Appendix.

- **Geographic Density:** Using Lightcast employment data, we measure the expected overall labor market density where an occupation's workers are located. Following Bleakley and Lin (2012), we use local employment density as a proxy for the breadth of local employment opportunities. For each occupation, we calculate the employment-weighted average of log overall CBSA density (total workers per square mile) across U.S. Core Based Statistical Areas:

  $$E[\log(\text{density})|\text{occupation}_x] = \sum_i \frac{\text{employment}_{ix}}{\text{total\_employment}_x} \times \log\left(\frac{\text{total\_employment}_i}{\text{area}_i}\right)$$

where employment_{ix} is employment in occupation x and CBSA i, and $\text{total\_employment}_i$ is total employment across all occupations in CBSA i. This captures whether an occupation's workers tend to be located in dense labor markets with more employment opportunities, not occupation-specific density. The log transformation reduces the influence of extreme high-density areas.

- **Age:** Using ACS microdata, we calculate each occupation's fraction of workers aged 55+, with higher shares reducing adaptive capacity given documented challenges older workers face in transitions. Alternative age specifications are examined in the Online Appendix.

For occupations missing O∗NET skill data (approximately 15% of occupations), we use k-nearest neighbors (KNN) imputation to estimate missing skill importance scores (see the Online Appendix for more details).

We then construct our adaptive capacity index by combining each component using employment-weighted Z-scores with winsorization, drawing on composite indicator guidelines (OECD and European Commission, Joint Research Centre 2008). To do so, for each occupation we: (1) winsorize component values at employment-weighted 1st and 99th percentiles, (2) compute Z-scores for each component relative to other occupations, reversing the age Z-score to reflect its negative contribution to adaptive capacity, (3) average the four Z-scores, and (4) transform the average of the Z-scores to a value between 0 and 1 by calculating the employment-weighted percentile ranking for each occupation's mean Z-score.

Following the spirit of similar policy-oriented indices, we remain agnostic about the relative contribution of each factor to occupation-level adaptive capacity. Alternative approaches could include expert weighting, PCA (explored in the Online Appendix), or empirical estimation using causal forests (Gulyas and Pytka 2019; Athey et al. 2024).

Adaptive capacity scores range from 0 to 1, where 0.75 indicates that the average worker in an occupation has higher adaptive capacity than 75% of U.S. workers. Unless otherwise stated, all correlations, quartiles, and percentiles in this paper are employment-weighted.

We test alternative specifications varying transferability measures, age measures, normalization methods, geographic density inclusion, routineness measures, and aggregation methods. These findings are largely robust across specifications. The positive correlation persists, and high-vulnerability workers remain concentrated in clerical rather than professional occupations (Online Appendix A.6).

4 Results

4.1 Relationship Between AI Exposure and Adaptive Capacity

We find a positive correlation between adaptive capacity and AI exposure (r = 0.502), indicating that workers in occupations with higher exposure tend to have higher adaptive capacity to recover from displacement. Of the 37.1 million workers in the top quartile of AI exposure, 26.5 million also have above-median adaptive capacity, leaving them relatively well-positioned to navigate job transitions if necessary. At the same time, 6.1 million workers (4.2% of the workforce in our sample) are both highly exposed and in the bottom quartile of adaptive capacity.

Figure 1 shows the relationship between our adaptive capacity index and the AI exposure measures from Eloundou et al. 2024. The positive correlation between exposure and adaptive capacity holds across alternative index specifications, with many administrative and clerical occupations consistently showing low adaptive capacity and high exposure. Professional and managerial occupations (56.9 million workers) have relatively higher adaptive capacity on average (0.734) despite substantial exposure (0.400), while administrative support occupations have lower adaptive capacity (0.360) combined with the highest AI exposure of any major occupation group (0.525). Together, administrative support (17.8 million workers) and sales (13.1 million workers) represent segments of the workforce with limited adaptive capacity while simultaneously facing substantial AI exposure (statistics by major occupation group shown in Online Appendix).

Occupations in the lower-right quadrant of Figure 1 represent above-median exposure and below-median adaptive capacity simultaneously, representing workers with the lowest adaptive capacity relative to their AI exposure. In contrast, those in the upper-right quadrant represent occupations with both high AI exposure and high adaptive capacity, indicating that they are relatively well-positioned to transition to new work if needed.

Table 1 presents the 15 occupations with the lowest adaptive capacity among those with high AI exposure (top quartile). These occupations combine high exposure to AI with characteristics that limit workers' ability to easily transition to new work if displaced.

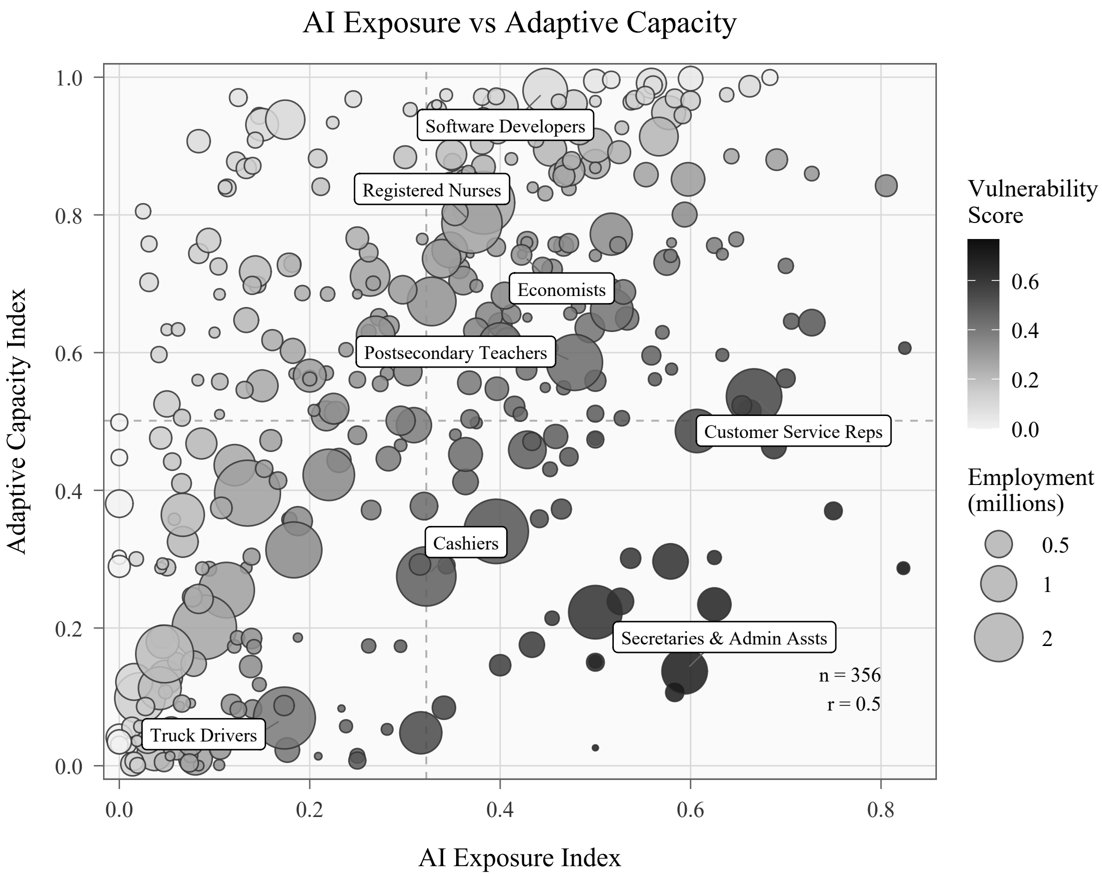

Figure 1: Relationship Between AI Exposure and Adaptive Capacity Index Across Occupations. Scatter plot shows correlation between Eloundou et al. (2024) AI exposure scores and a composite index of occupation-level adaptive capacity factors. For visualization purposes, we define vulnerability score = $\sqrt{(1 - \text{AC}) \times \text{AI Exposure}}$; darker shading indicates higher vulnerability (high exposure combined with low adaptive capacity). Employment-weighted correlation r = 0.502. Lower-right quadrant shows high exposure with low adaptive capacity.

In contrast, occupations with low AI exposure but high adaptive capacity (shown in Online Appendix) are predominantly manual, skilled trades including electricians, firefighters, and health technicians.

Table 2 presents the 15 occupations with the highest adaptive capacity among those with high AI exposure (top quartile). Notably, some well-compensated roles like accountants, computer programmers, and financial advisors rank only moderately on adaptive capacity among highly exposed occupations, as their relatively specialized skill sets or older age profiles limit their adaptive capacity scores despite high net liquid wealth.

Table 1: Occupations with Lowest Adaptive Capacity Among High AI Exposure (Top Quartile)

Occupation	Exposure (%)	AC (%)	Emp.
Door-to-door sales workers, news and street vendors	50	3	5K
Court, municipal, and license clerks	58	11	170K
Secretaries and administrative assistants, except legal, medical, and executive	59	14	1.7M
Payroll and timekeeping clerks	50	15	157K
Property appraisers and assessors	50	15	59K
Tax examiners and collectors, and revenue agents	62	18	54K
Eligibility interviewers, government programs	59	18	156K
Office clerks, general	50	22	2.5M
Medical secretaries and administrative assistants	62	23	831K
Insurance sales agents	53	24	469K
Interpreters and translators	82	29	53K
Receptionists and information clerks	58	30	965K
Insurance claims and policy processing clerks	54	30	229K
Tax preparers	62	30	74K
Legal secretaries and administrative assistants	75	37	155K

High AI exposure defined as top quartile of occupations (exposure $\geq$ 46%). Adaptive capacity ranges from 0 to 1 (higher = better positioned).

Table 2: Occupations with Highest Adaptive Capacity Among High AI Exposure (Top Quartile)

Occupation	Exposure (%)	AC (%)	Emp.
Web and digital interface designers	68	100	111K
Marketing managers	60	100	385K
Producers and directors	52	100	145K
Financial and investment analysts	50	99	341K
Computer and information systems managers	56	99	646K
Computer network architects	56	99	177K
Other mathematical science occupations	66	99	270K
Web developers	64	97	79K
Other life scientists	55	97	175K
Other financial specialists	58	97	184K
Information security analysts	54	97	179K
Software quality assurance analysts and testers	60	97	200K
Computer and information research scientists	50	97	38K
Chemists and materials scientists	46	96	92K
Public relations and fundraising managers	54	96	113K

High AI exposure defined as top quartile of occupations (exposure $\geq$ 46%). Adaptive capacity ranges from 0 to 1 (higher = better positioned).

4.2 Components of Adaptive Capacity

Table 3 presents the correlations between AI exposure and the four components of our adaptive capacity index. The correlations reveal distinct patterns that illuminate how different dimensions of adaptive capacity relate to AI exposure.

Table 3: Correlation Matrix: AI Exposure and Adaptive Capacity Components

Variable	(1)	(2)	(3)	(4)	(5)
(1) AI Exposure	1.00				
(2) Transferability	0.23	1.00			
(3) Net Liquid Wealth	0.59	0.36	1.00		
(4) Worker Density	0.43	0.13	0.36	1.00	
(5) Share 55+	0.15	0.09	0.25	0.11	1.00

Employment-weighted Pearson correlations. Transferability = growth-weighted skill and work activity transferability. Net liquid wealth = log median net liquid wealth by occupation. Worker density = log expected geographic worker density. Share 55+ = fraction of workers aged 55 or older.

Net liquid wealth shows the strongest correlation with AI exposure (r = 0.591), followed by geographic worker density (r = 0.426), skill transferability (r = 0.227), and age (r = 0.152). Among the components themselves, wealth exhibits moderate correlations with transferability (r = 0.360), density (r = 0.355), and age (r = 0.253). The remaining pairwise correlations are weaker: transferability with density (r = 0.126) and age (r = 0.092), and density with age (r = 0.108).

4.3 Geographic Distribution of Adaptive Capacity

We examine geographic variation by matching our occupation-level measures to metropolitan statistical area (MSA) employment data from Lightcast. For each of 927 metropolitan and micropolitan areas, we calculate the share of workers in occupations with both high AI exposure (top quartile) and low adaptive capacity (bottom quartile).

Figure 2 shows variation across metropolitan areas, with shares ranging from 2.4% to 6.9% and a national average of 3.9%. However, the distribution is fairly compressed—90% of MSAs fall between 3.1% and 5.2%, indicating vulnerability is spread relatively evenly across U.S. labor markets rather than concentrated in specific regions.

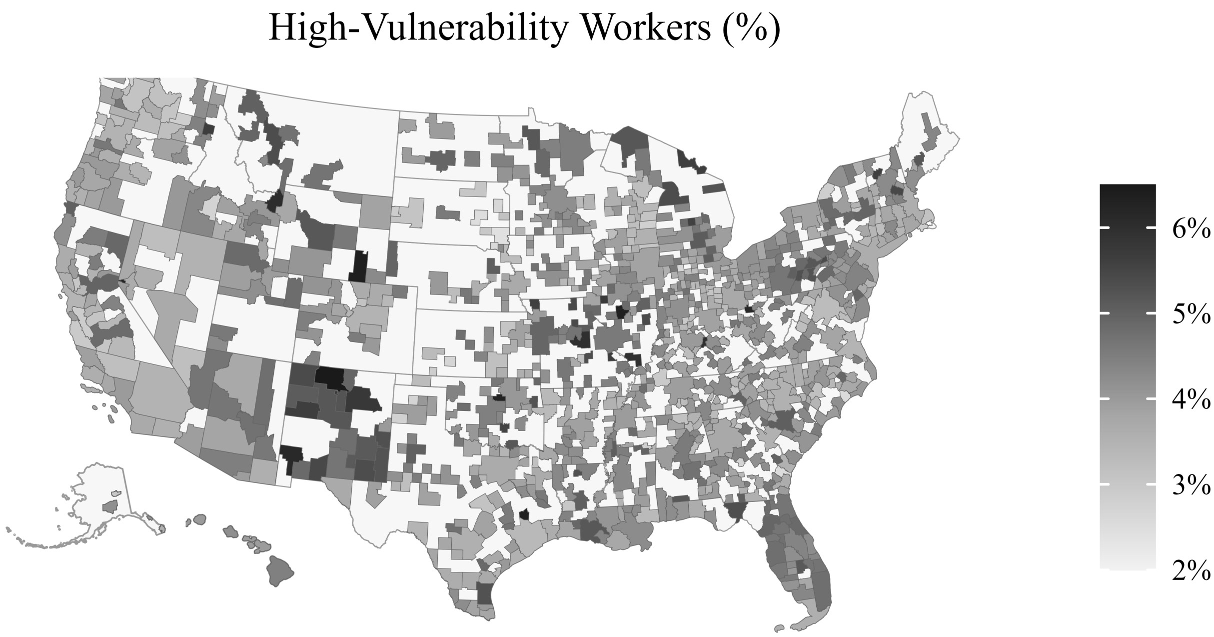

Figure 2: Geographic Distribution of High Exposure, Low Adaptive Capacity Occupations. Share of workers in top quartile AI exposure and bottom quartile adaptive capacity (927 metropolitan and micropolitan areas). The highest vulnerability shares appear in college towns and state capitals, where administrative and clerical positions supporting institutional employers are concentrated.

The highest vulnerability shares appear in college towns (Laramie WY, Huntsville TX, Stillwater OK), state capitals (Springfield IL, Carson City NV, Frankfort KY), and small towns in New Mexico and Oklahoma. These communities share concentrations of administrative and clerical positions supporting institutional employers like universities, state government offices, and regional service centers. Technology hubs show consistently low shares: San Jose (2.9%), Seattle (3.1%), and San Francisco (3.4%) all fall below the national average, reflecting workforces with higher savings and more diverse skill portfolios.[1]

[1] The national average for MSAs may differ from the overall workforce average as MSA data excludes rural areas and smaller metros.

5 Limitations

Our approach has several important limitations. First of all, our adaptive capacity index measures where displacement costs may differ across occupations, but neither this index nor AI exposure measures can predict displacement likelihood. Recent work by Autor and Thompson (2025) and Brynjolfsson et al. (2025) explores how exposure can translate into different employment and wage effects for different workers, but a strong predictive measure of displacement risk remains elusive. Because no such measure yet exists, we present our adaptive capacity index alongside a common measure of AI exposure in order to show the overlap between the potential for AI to cause change to an occupation and the ability of workers in that occupation to manage a job transition if exposure ultimately leads to displacement.

Moreover, our adaptive capacity estimates derive primarily from partial equilibrium evidence on displacement costs. If AI fundamentally reshapes the economy, altering skill premia, geographic patterns, or labor's share of income, these historical relationships may not hold. General equilibrium effects could either amplify or dampen the adaptive capacity differences we identify, particularly if AI adoption occurs rapidly across sectors. For instance, if many displaced clerical workers transition to child care, this influx could reshape both occupations' vulnerability profiles even though child care itself has low AI exposure. Alternatively, if Transformative AI were to make entire skills redundant across many occupations, then workers with high skill transferability today might face different labor market options in the future.

Beyond these conceptual limitations, occupation-level aggregation masks within-occupation heterogeneity in adaptive capacity. Workers within the same occupation vary substantially in financial resources, skills, and other characteristics affecting their ability to adapt. Future research using individual-level data could more precisely identify populations with varying adaptive capacity.

Additionally, collapsing multiple dimensions into a single index loses component-specific information. We decided to use equal weighting of factors for simplicity and transparency, though components may contribute unequally to displacement costs in reality. Alternative approaches like Delphi techniques or the causal forests approach in Athey et al. (2024) could potentially provide data-driven weights for some factors.

Technical challenges also arise from harmonizing occupational classifications across federal datasets with different sampling frames. OEWS and O*NET target occupation-level representativeness while SIPP targets demographic representativeness, affecting our net liquid wealth estimates for occupations with limited SIPP responses.

Finally, our analysis provides a current snapshot, but both AI adoption and worker adaptive capacity evolve over time. As AI technologies mature and workers gain experience, the relationship between exposure and labor market outcomes will likely shift. Financial circumstances, skill development, and labor market conditions continuously evolve, altering which populations are most resilient to technological disruption over time.

6 Conclusion

This paper demonstrates that, on average, U.S. workers most exposed to AI are better positioned to navigate job transitions following displacement than the broader workforce. We find a positive correlation (r = 0.502) between AI exposure and a novel measure of worker adaptive capacity to displacement. Higher-income, highly skilled workers in professional occupations – who rank highest in existing AI exposure measures – typically possess characteristics that enable successful navigation of job transitions, such as substantial financial resources and transferable skill sets. Managerial, professional, and technical occupations like computer support specialists and analyst roles show both high AI exposure and high adaptive capacity, whereas many clerical and administrative workers face similar levels of exposure without the same buffers to support smooth transitions if displaced. Despite the overall positive correlation between exposure and adaptive capacity, we identify 6.1 million workers (4.2% of the workforce in our sample) whose occupations fall in the top quartile of AI exposure but the bottom quartile of adaptive capacity. These workers are concentrated in clerical, administrative support, and assistance roles, and they represent a segment of the labor market that may struggle most to transition to comparable new job opportunities if displaced.

More broadly, this study contributes to the literature on AI's labor market impacts by introducing a framework that presents technological exposure alongside a composite measure of worker characteristics that can shape displacement costs. In doing so, we provide one lens for understanding where the welfare costs of AI-driven disruption may be concentrated in the cases where AI exposure translates to job loss.

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