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

Online Appendix

Sam Manning Tomás Aguirre

January 9, 2026

This appendix is organized as follows: Section A provides further methodological details on occupational crosswalks, sample construction, skill transferability calculations, and data quality procedures. Section B reviews the literature on additional factors that may influence adaptive capacity but are not included in our main specification. Section C presents additional results, including subgroup analyses by occupation group, component breakdowns for major occupations, and geographic distribution of high-vulnerability workers. Section D reports robustness checks examining the sensitivity of our main findings to alternative specifications, weighting schemes, and threshold definitions.

A Further Methodological Details

A.1 Occupational Crosswalk Details

This appendix provides detailed information on the occupational crosswalks used to harmonize data across different classification systems. We integrate data from multiple national sources into our final harmonized occupation taxonomy.

A.1.1 O∗NET/SOC to OEWS

For AI exposure and skills data, we begin with O∗NET occupations, focusing exclusively on standard SOC codes (those ending with ".00"). We map these SOC codes to OEWS categories, using total employment from OEWS to create weighted averages when the mapping is not one-to-one.[1]

A.1.2 Lightcast to OEWS

For geographic density data, we utilize occupation-level employment data from Lightcast. Lightcast uses its own proprietary taxonomy (Lightcast SOC 2021), which is designed to be closely aligned with the OEWS and the 2018 SOC System. We map Lightcast codes to their OEWS counterparts to ensure consistency with our main occupation categories, following the chain Lightcast → OEWS → Modified SIPP. Further details on Lightcast SOC particularities, such as aggregations for military and postsecondary teaching occupations, are provided by Lightcast (2023).

A.1.3 Census to SIPP

For demographic data from household surveys, we work with Census occupation codes and map them to SIPP codes. While Census and SIPP codes largely overlap, SIPP uses a more aggregate classification for certain occupations—for example, SIPP code 0010 combines Census codes for both chief executives (0010) and legislators (0030).

A.1.4 Modified SIPP

To bridge OEWS and SIPP taxonomies while preserving the most granular occupation level possible, we create Modified SIPP codes. This includes three modifications that aggregate occupations differently classified between systems: 05MM (combining buyers and purchasing agents), 200M (combining counselors), and 36MM (combining home health and personal care aides).[2] Modified SIPP represents our final harmonized occupation taxonomy used for all analyses.

[1] The SOC and OEWS classifications are nearly identical, but OEWS aggregates certain detailed occupations. Following Hopson (2021), we handle these aggregations using employment weights. For example, OEWS code 13-1020 "Buyers and purchasing agents" combines three SOC codes with weights based on May 2016 employment.

[2] Modified SIPP code 05MM aggregates SIPP codes 0510, 0520, and 0530 to align with OEWS 13-1020. Modified SIPP code 200M combines SIPP codes 2001 and 2004 to align with OEWS 21-1018. Modified SIPP code 36MM aggregates SIPP codes 3601 and 3602 to align with OEWS 31-1120. These modifications ensure consistent occupation definitions across our data sources.

A.2 Sample Construction

Our occupation sample is constructed through data-driven filtering based on data availability. The SIPP classification includes 523 occupation categories. After merging with AI exposure data from Eloundou et al. (2024), 356 occupations have complete demographic and employment data.

Occupations without AI exposure scores are excluded from the analysis. Excluded occupations predominantly consist of residual "all other" categories—catch-all classifications such as "Computer occupations, all other" (SIPP 1108) that combine heterogeneous occupations without consistent O∗NET mappings for skills or AI exposure measurement.

A.3 Skill Transferability Calculation Example

To illustrate the growth-weighted skill transferability calculation described in the Methodology section, we provide a worked example for "Office Clerks, General" (Modified SIPP 5860).

The transferability formula is:

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

For Office Clerks, the calculation proceeds as follows:

1. *Extract skill profile.* Load O∗NET Skills and Work Activities importance scores (e.g., Active Listening: 3.88, Speaking: 3.75).
2. *Normalize.* Apply employment-weighted percentile normalization to each skill dimension.
3. *Compute similarity.* Calculate cosine similarity with all other occupations. Top matches: Secretaries (0.987), Bookkeeping (0.976), Customer Service (0.958).
4. *Apply growth weighting.* Weight each similarity by the destination occupation's employment and projected growth rate based on BLS employment projections.
5. *Aggregate.* The sum of weighted similarities divided by total weighted employment yields the final transferability score.

This low transferability score (24.3rd percentile) reflects that Office Clerks' skills primarily transfer to other declining administrative occupations, limiting adaptation opportunities.

A.4 KNN Imputation Validation

Approximately 15% of occupations in our sample lack O∗NET skills data required for transferability calculations. For these occupations, we apply k-nearest neighbors (KNN) imputation using occupation embeddings generated from O∗NET occupation descriptions.

Imputation Process:

Our imputation process uses the E5-large language model (Wang et al. 2022) to generate embeddings from O∗NET occupation descriptions, identifies the 10 most similar occupations via cosine similarity of these embeddings, and imputes missing values as similarity-weighted averages of the 10 most similar occupations. 5-fold cross-validation (each fold testing on 20% of occupations) showed k=10 minimized Mean Absolute Error averaged across Skills and Work Activities components.

Validation Methodology: We use 5-fold cross-validation to select the optimal number of neighbors:

1. *Partition.* Divide occupations with known O∗NET data into 5 folds, ensuring each occupation appears in exactly one test fold.
2. *Cross-validate.* For each fold, train on the remaining 4 folds and evaluate on the held-out fold.
3. *Impute.* For each held-out occupation, identify k nearest neighbors from the training occupations via cosine similarity and impute skills as their weighted average.
4. *Select k.* Choose the value that minimizes Mean Absolute Error averaged across all folds and both Skills and Work Activities components.

Validation Results:

- Baseline (mean imputation): MAE = 1.07 (on 1-5 scale)
- KNN (k=10): MAE = 0.58 (on 1-5 scale)
- Improvement over baseline: 45%
- Correlation between imputed and actual: 0.92

- Transferability score correlation: 0.85

The high correlation (0.85) between transferability scores calculated from imputed versus actual skills data suggests the imputation preserves the key relationships needed for our analysis.

A.5 Data Quality and Coverage

Our analysis relies on harmonizing data across multiple national surveys with different sampling frames and coverage. Table 1 summarizes the data availability and quality filters applied.

Table 1: Data Coverage and Quality Filters

Filter Stage	Occupations	Employment Coverage
Initial O*NET/OEWS universe	831	154.2M (100.0%)
After SOC to Modified SIPP mapping	523	154.2M (100.0%)
After requiring ≥15 SIPP observations	369	149.9M (97.2%)
After requiring non-missing wealth data	369	149.9M (97.2%)
After requiring skills data (including imputed)	367	149.9M (97.2%)
After requiring AI exposure data	356	147.9M (95.9%)
Final sample	356	147.9M (95.9%)

Employment figures from May 2024 OES. SIPP observation threshold ensures reliable wealth estimates. O*NET data (skills, work activities, knowledge, abilities) imputed via K-nearest neighbors for occupations lacking direct coverage.

The SIPP sample sizes vary considerably across occupations, from the minimum threshold of 15 observations (pooled across 2022–2024) to over 1,000 for large occupations like registered nurses and elementary school teachers. Occupations excluded due to insufficient SIPP observations primarily consist of highly specialized roles with small employment bases, such as specific types of engineers, scientists, and technicians.

B Literature Review on Other Factors Driving Adaptive Capacity

Several factors not included in the main specification for the adaptive capacity index likely influence a worker's capacity to adapt to displacement shocks. Below, we review the literature on routine task intensity, income, and union representation.

B.1 Routine Task Intensity

Routine task intensity may be another factor that shapes workers' adaptive capacity. The concept of task routineness was developed by Autor et al. (2003), who demonstrated that computer capital substitutes for workers in routine tasks—those involving explicit, codifiable procedures—while complementing workers in nonroutine cognitive tasks. Goos and Manning (2007) independently studied similar patterns in the UK, finding evidence of job polarization where middle-skilled occupations declined while both high- and low-skilled occupations grew. These authors used this framework to explain skill polarization: why middle-skilled workers have experienced downward wage pressure as information and communication technologies are substitutive for routine tasks, but complementary to abstract-intensive tasks and have little effect on manual-intensive tasks. They identified routine tasks by examining the prevalence of repetitive, rule-following activities across different occupations.

Autor and Dorn (2013) developed the Routine Task Intensity (RTI) measure to capture how much an occupation relies on routine, predictable tasks versus manual or abstract work. Occupations high in RTI—such as data entry clerks, bookkeepers, and assembly line workers—perform repetitive tasks that follow explicit rules and procedures, making them particularly susceptible to computerization. In contrast, occupations requiring physical adaptability (like plumbers or nurses) or abstract reasoning (like managers or engineers) score lower on RTI. Over the past two decades, research has shown that workers in routine-intensive occupations face persistent challenges: their wages have stagnated or declined, job quality has deteriorated, and employment opportunities have shrunk as technology advances. An emerging set of recent studies suggests that when these workers lose their jobs, they experience severe and lasting consequences—longer unemployment spells, larger wage losses upon reemployment, and more difficulty transitioning to new occupations—precisely because their routine-focused skills transfer poorly to other available jobs in an increasingly automated economy. This theory suggests that RTI may influence a worker's adaptive capacity through a skill transferability channel (a core factor included in our main adaptive capacity index).

Blien et al. (2021) found that workers in more routine-intensive occupations experience substantially larger displacement costs following mass layoffs in Germany, though the effects operated primarily through extended unemployment duration rather than reduced wages. Workers with one percentage point higher routine intensity experienced an additional 0.39 percentage point quarterly earnings reduction over 24 quarters post-displacement, or approximately €1,000 in additional losses over six years per percentage point of routine intensity. Yakymovych (2022) extended these results using administrative data from Sweden, finding that routine workers lose an additional year's worth of pre-displacement earnings and spend 180 more days in unemployment compared to displaced non-routine workers, with effects persisting for eight years. In a detailed analysis of heterogeneous displacement effects also leveraging Swedish data, Athey et al. (2024) identified older workers in routine-intensive jobs as facing the most predictable and severe displacement effects, though it is unclear the extent to which each factor drives these effects, and how much the effect of RTI is accounted for by broader skill transferability.

B.2 Income

Income represents another potential factor shaping adaptive capacity to displacement, but the evidence remains mixed. Earlier literature typically found that higher-earning workers experience larger displacement costs. As Jacobson et al. (2011, p. 5) note, displacement costs "are usually small for low-wage and low-tenured workers," with high-wage, high-tenure workers suffering the largest absolute earnings losses. This pattern reflects that high earners may possess more firm- or industry-specific human capital that loses value upon job loss, and they face larger absolute earnings shocks.

However, more recent studies complicate this picture. Guvenen et al. (2017) show that scarring from non-employment is largest for both low-income workers and those in the top 5 percent of the earnings distribution, suggesting a non-linear relationship. Athey et al. (2024) find that low-income workers in Sweden suffer comparatively more from displacement when considering relative losses, while Rose and Shem-Tov (2024) report broadly similar costs across income groups once accounting for other worker characteristics. Evidence on the mechanisms further complicates interpretation: d'Adda et al. (2025) find that while networks facilitate reemployment for both manual and cognitive workers following mass layoffs, they create different trade-offs—networks help manual workers find jobs faster but channel them into different occupations, leading to wage penalties, while cognitive workers experience smaller reemployment gains but maintain better wage outcomes.

These competing effects may stem partly from the various factors that income proxies for beyond immediate financial resources. Higher-income workers often enjoy advantages including social capital, career capital, and institutional knowledge that can ease reemployment. Job search frequently occurs through personal networks rather than formal channels (Granovetter 1995), and higher-income workers typically have access to broader and more valuable networks. Building on this insight, Calvó-Armengol and Jackson (2004) demonstrate theoretically that well-connected workers enjoy persistent employment advantages, while Ioannides and Loury (2004) document empirically that individuals in higher-income neighborhoods and occupations benefit from superior job-information networks. Higher-income workers are also more likely to use private placement agencies and professional networks rather than public employment services, which are associated with higher-quality job matches (Addison and Portugal 2002).

Given these conflicting pathways, we exclude income from our main adaptive capacity index. While income undoubtedly proxies for advantages such as social networks, career capital, and geographic mobility (Bound and Holzer 2000), the empirical record does not consistently show that higher income reduces displacement costs overall.

B.3 Union Representation and Collective Protection

Unions play a complex role in how workers experience technological change. On one hand, they typically raise wages and improve working conditions for their members. On the other hand, these wage premiums can accelerate employment declines in exposed occupations. Kostøl and Svarstad (2023) found that unions raise the relative wages of routine workers but may inadvertently reduce demand for these positions. Similarly, Parolin (2021) observed that higher union coverage inhibits earnings declines but can accelerate employment share declines in automation-exposed occupations.

The protection unions provide isn't evenly distributed. Lee and Kim (2023) found that unions primarily protect incumbent workers, particularly senior skilled workers, sometimes at the expense of younger or less-skilled employees. Haapanala et al. (2022) noted similar patterns, with stronger unions associated with greater employment declines for young and low-educated workers when faced with technological change.

Notably, unions do not simply resist the adoption of new technologies. Belloc et al. (2022) found a positive association between employee representation and the adoption of advanced technologies, suggesting that unions can facilitate technological change when they can shape its implementation to benefit their members. Given this complex nature of the impact of unions, we do not directly incorporate it in our adaptive capacity index.

C Subgroup Analysis

C.1 Adaptive Capacity and AI Exposure by Major Occupation Group

Employment-weighted averages of adaptive capacity and AI exposure vary substantially across major occupation groups in our sample, with professional and managerial occupations showing the highest adaptive capacity while administrative support occupations combine low adaptive capacity with the highest AI exposure across all groups.

C.2 Component Values for Largest Occupations

Table 2 presents the four adaptive capacity components and overall index values for the 50 largest occupations by employment. This detailed breakdown allows examination of which specific factors drive adaptive capacity in major occupations discussed in the main text.

The variation across components within occupations illustrates why composite indices can mask important heterogeneity. For instance, while both software developers and registered nurses show high overall adaptive capacity, their underlying drivers differ substantially—software developers benefit from exceptionally high net liquid wealth and a favorable age profile, while registered nurses combine moderate wealth with top tier skill transferability.

C.3 Detailed Component Relationships

Figure 1 presents the complete pairwise relationships between AI exposure and the four adaptive capacity components. The scatter plot matrix shows employment-weighted scatter plots (lower triangle), density distributions (diagonal), and correlations (upper triangle).

C.4 Occupations with Low AI Exposure and High Adaptive Capacity

The following table presents occupations that have both low AI exposure (bottom quartile) and high adaptive capacity (top quartile).

These occupations employ 1.7 million workers.

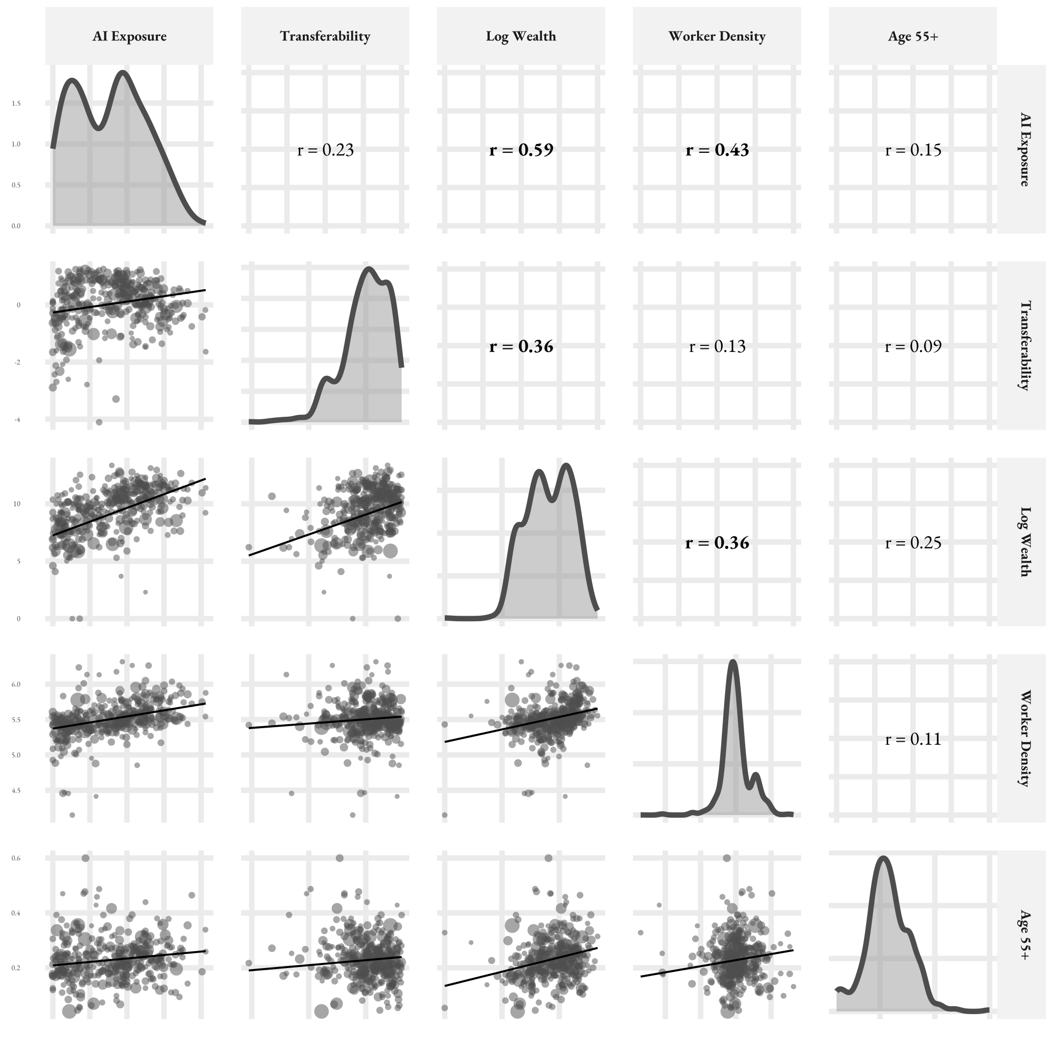

Figure 1: Detailed Pairwise Relationships Between AI Exposure and Adaptive Capacity Components. Lower triangle: scatter plots with employment-weighted regression lines. Upper triangle: employment-weighted Pearson correlations. Diagonal: employment-weighted density distributions. Net liquid wealth (r = 0.591) and geographic density (r = 0.426) show strong positive associations with AI exposure.

Table 2: Component Values for the 50 Largest Occupations by Employment

Occupation	Emp.	Trans.	Wealth	Density	Age 55+	AI Exp.	AC
Home health and personal care aides	3988	1.20	0.4	5.78	0.35	0.13	0.40
Retail salespersons	3800	0.39	3	5.42	0.24	0.40	0.34
Fast food and counter workers	3781	-1.98	0.6	5.39	0.04	0.09	0.20
General and operations managers	3584	1.00	56	5.51	0.22	0.38	0.82
Driver/sales workers and truck drivers	3482	-0.67	4	5.34	0.30	0.17	0.07
Registered nurses	3282	1.36	44	5.48	0.23	0.37	0.79
Cashiers	3170	-0.23	0.6	5.36	0.16	0.32	0.28
Laborers and freight, stock, and materia...	2983	-1.74	2	5.45	0.18	0.05	0.16
Postsecondary teachers	2793	0.27	160	5.49	0.31	0.48	0.59
Stockers and order fillers	2780	-0.06	2	5.41	0.18	0.18	0.31
Cooks	2744	0.17	0.3	5.37	0.17	0.11	0.26
Customer service representatives	2726	-0.00	5	5.52	0.20	0.67	0.54
Office clerks, general (H)	2511	-0.06	6	5.46	0.31	0.50	0.22
Waiters and waitresses	2303	-1.28	0.7	5.49	0.07	0.22	0.42
Janitors and building cleaners	2216	-0.65	2	5.53	0.34	0.02	0.10
Elementary and middle school teachers	2028	0.54	30	5.44	0.20	0.33	0.67
Secretaries and administrative assistant... (H)	1738	-0.69	15	5.44	0.36	0.59	0.14
Software developers	1654	-0.55	150	5.96	0.13	0.45	0.98
Sales representatives, wholesale and man...	1561	-0.38	85	5.56	0.32	0.61	0.49
Maintenance and repair workers, general	1532	0.83	10	5.42	0.31	0.07	0.36
Teaching assistants	1530	0.52	6	5.55	0.20	0.40	0.61
Other assemblers and fabricators	1509	-0.46	4	5.24	0.25	0.04	0.11
First-line supervisors of office and adm...	1496	0.98	41	5.55	0.29	0.52	0.66
Bookkeeping, accounting, and auditing cl...	1456	-1.26	26	5.45	0.42	0.32	0.05
Accountants and auditors	1448	0.30	92	5.69	0.26	0.52	0.77
Nursing assistants	1388	0.47	2	5.41	0.21	0.12	0.44
Security guards and gambling surveillanc...	1252	1.23	3	5.80	0.28	0.26	0.71
Supervisors of transportation and materi...	1231	1.69	10	5.79	0.22	0.17	0.94
Sales representatives of services, excep...	1189	0.80	52	5.76	0.23	0.57	0.91
First-line supervisors of food preparati...	1187	1.23	2	5.39	0.14	0.27	0.63
Secondary school teachers	1177	1.32	44	5.39	0.21	0.34	0.74
First-line supervisors of retail sales w...	1113	0.39	11	5.36	0.22	0.43	0.46
Construction laborers	1058	-0.51	0.3	5.33	0.17	0.02	0.12
Project management specialists	1006	1.06	80	5.74	0.21	0.40	0.96
Human resources workers	982	0.05	31	5.64	0.19	0.35	0.75
Receptionists and information clerks	965	-0.93	5	5.53	0.22	0.58	0.30
Other teachers and instructors	951	0.03	21	5.53	0.28	0.31	0.49
Landscaping and groundskeeping workers	943	-2.99	2	5.40	0.23	0.04	0.02
Management analysts	894	0.32	105	5.86	0.28	0.50	0.90
Food preparation workers	889	-1.72	0.6	5.50	0.18	0.05	0.13
Market research analysts and marketing s...	861	-0.47	32	5.83	0.12	0.58	0.95
Shipping, receiving, and inventory clerks	858	0.65	6	5.46	0.26	0.36	0.45
Maids and housekeeping cleaners	855	-1.91	0.2	5.49	0.30	0.08	0.01
Computer support specialists	844	0.81	34	5.62	0.20	0.60	0.85
Medical secretaries and administrative a... (H)	831	-0.33	4	5.52	0.30	0.62	0.23
Financial managers	819	0.13	119	5.82	0.25	0.45	0.89
First-line supervisors of construction t...	806	1.46	19	5.35	0.27	0.20	0.57
Industrial truck and tractor operators	806	-0.57	5	5.31	0.22	0.05	0.18
Lawyers, and judges, magistrates, and ot...	797	-0.30	307	5.91	0.34	0.36	0.85
Medical assistants	793	1.56	15	5.48	0.11	0.15	0.93

Trans. = growth-weighted skills and work activities transferability (z-score). Wealth = median net liquid wealth in thousands of dollars (log-transformed in index). Density = log expected geographic worker density. Age 55+ = fraction of workers aged 55+ (%). AI Exp. = AI exposure (employment-weighted percentile). AC = adaptive capacity index (0-1 scale, employment-weighted percentile). Employment in thousands. (H) = high-vulnerability occupation (top quartile AI exposure and bottom quartile adaptive capacity).

C.5 Complete List of High-Vulnerability Occupations

Table 4 presents all occupations in the top quartile for AI exposure and bottom quartile for adaptive capacity. This complete list expands on the summary statistics presented in the main text.

Table 3: Occupations with Low AI Exposure and High Adaptive Capacity

Occupation	Exposure (%)	AC (%)	Emp.
Dental assistants	9	76	375K
Firefighters	8	91	332K
Other protective service workers	13	87	227K
Miscellaneous health technologists and technicians	12	88	195K
Physician assistants	12	97	156K
Physical therapist assistants and aides	11	84	152K
Surgical technologists	3	76	114K
Telecommunications line installers and repairers	2	81	98K
Skincare specialists	11	84	70K

Low AI exposure = bottom quartile of occupations (exposure $\leq$ 13%). High adaptive capacity = top quartile of occupations (AC $\geq$ 75%). These occupations face low AI disruption risk and workers have high capacity to adapt.

Table 4: All Occupations with High AI Exposure and Low Adaptive Capacity

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

Complete list of high-vulnerability occupations (n = 10). High vulnerability = simultaneously in the top quartile of AI exposure and the bottom quartile of adaptive capacity.

The classification of high-vulnerability occupations uses employment-weighted quartiles, ensuring that thresholds reflect where most workers are concentrated rather than treating all occupations equally. This employment-weighted approach identifies 6.1 million workers (4.2% of the workforce) in occupations combining top-quartile AI exposure with bottom-quartile adaptive capacity.

C.6 Geographic Distribution of High-Vulnerability Occupations

The following tables present the geographic distribution of workers in occupations that are in the top quartile for AI exposure and bottom quartile for adaptive capacity. These occupations employ 6.1 million workers nationally, with substantial variation in their concentration across metropolitan and micropolitan statistical areas.

Table 5: Top 20 Metropolitan Statistical Areas by Employment in High-Vulnerability Occupations

Rank	Metropolitan Statistical Area	Employment	Share (%)
1	New York-Newark-Jersey City, NY-NJ-PA	374,512	3.6
2	Los Angeles-Long Beach-Anaheim, CA	281,166	4.0
3	Chicago-Naperville-Elgin, IL-IN-WI	191,008	3.8
4	Dallas-Fort Worth-Arlington, TX	163,513	3.7
5	Miami-Fort Lauderdale-Pompano Beach, FL	151,781	4.8
6	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	139,527	4.4
7	Houston-The Woodlands-Sugar Land, TX	121,709	3.3
8	Atlanta-Sandy Springs-Alpharetta, GA	118,217	3.7
9	Washington-Arlington-Alexandria, DC-VA-MD-WV	117,514	3.3
10	Boston-Cambridge-Newton, MA-NH	108,444	3.6
11	Phoenix-Mesa-Chandler, AZ	97,888	3.8
12	San Francisco-Oakland-Berkeley, CA	93,850	3.4
13	Minneapolis-St. Paul-Bloomington, MN-WI	89,056	4.2
14	Detroit-Warren-Dearborn, MI	82,807	3.9
15	Tampa-St. Petersburg-Clearwater, FL	75,127	4.8
16	Seattle-Tacoma-Bellevue, WA	72,813	3.1
17	St. Louis, MO-IL	68,349	4.6
18	San Diego-Chula Vista-Carlsbad, CA	67,009	3.7
19	Orlando-Kissimmee-Sanford, FL	66,790	4.4
20	Riverside-San Bernardino-Ontario, CA	65,949	3.5

High-vulnerability occupations defined as those simultaneously in the top quartile of AI exposure and the bottom quartile of adaptive capacity. Employment counts represent workers in these occupations within each MSA.

Table 6: Top 40 Metropolitan Statistical Areas by Share of Workers in High-Vulnerability Occupations

Rank	Metropolitan Statistical Area	Share (%)	Emp.	Rank	Metropolitan Statistical Area	Share (%)	Emp.
1	Atchison, KS	6.9	456	21	Barre, VT*	5.6	2,134
2	Española, NM	6.5	715	22	Maryville, MO†	5.6	551
3	Laramie, WY†	6.4	1,296	23	Mount Pleasant, MI†	5.6	1,663
4	Springfield, IL*	6.4	8,773	24	Ada, OK†	5.5	1,217
5	Huntsville, TX†	6.3	1,848	25	Concord, NH*	5.4	4,723
6	Stillwater, OK†	6.3	2,652	26	Las Cruces, NM†	5.4	4,965
7	Carson City, NV*	6.3	2,127	27	Kirksville, MO†	5.4	639
8	Silver City, NM†	6.1	657	28	Charleston-Mattoon, IL†	5.4	1,599
9	Athens, OH†	6.1	1,611	29	Moberly, MO	5.4	589
10	Rexburg, ID†	6.1	1,907	30	Farmington, NM	5.4	2,723
11	Frankfort, KY*	6.0	2,511	31	Lewisburg, PA†	5.4	1,081
12	Jefferson City, MO*	6.0	5,050	32	Helena, MT*	5.4	2,528
13	Carbondale-Marion, IL†	6.0	3,748	33	Traverse City, MI	5.4	4,072
14	Los Alamos, NM‡	5.8	1,307	34	Carlsbad-Artesia, NM	5.4	1,809
15	Las Vegas, NM†	5.8	566	35	Rolla, MO†	5.3	1,134
16	Macomb, IL†	5.8	721	36	Tallahassee, FL*	5.3	11,228
17	Farmington, MO	5.7	1,404	37	Portales, NM†	5.3	396
18	Moscow, ID†	5.7	996	38	Ruston, LA†	5.3	1,134
19	Grants, NM	5.6	434	39	Johnstown, PA†	5.3	2,768
20	Sault Ste. Marie, MI	5.6	780	40	Kingsville, TX†	5.3	749

*State capital; †College town; ‡Federal research center. Share represents the percentage of total MSA employment in high-vulnerability occupations (simultaneously in the top quartile of AI exposure and the bottom quartile of adaptive capacity). Emp. = employment in high-vulnerability occupations.

C.7 State-Level Geographic Patterns

While the main analysis focuses on metropolitan statistical areas, state-level aggregation provides additional policy-relevant geographic variation. Table 7 presents the share of workers in high-vulnerability occupations by state.

Table 7: State-Level Concentration of High-Vulnerability Workers

State	Share (%)	Workers	State	Share (%)	Workers
New Mexico	5.3	51,814	Montana	4.8	28,881
Missouri	4.8	156,697	Florida	4.6	506,183
New Hampshire	4.6	35,171	Pennsylvania	4.6	302,826
Delaware	4.5	23,050	Wyoming	4.4	14,033
Oklahoma	4.4	84,274	Idaho	4.3	42,114
Louisiana	4.3	93,926	South Carolina	4.3	109,952
Minnesota	4.3	139,022	North Dakota	4.3	21,157
Michigan	4.2	204,766	Alabama	4.2	99,601
Hawaii	4.2	31,925	Utah	4.2	78,718
Maine	4.1	30,486	Rhode Island	4.1	22,535
Illinois	4.1	269,260	Tennessee	4.1	148,882
Indiana	4.1	142,148	West Virginia	4.0	30,746
Vermont	4.0	14,414	Kentucky	4.0	89,873
Nebraska	4.0	46,506	Arizona	4.0	141,427
Kansas	4.0	64,543	Mississippi	4.0	52,543
Ohio	4.0	239,496	Connecticut	4.0	74,173
Iowa	3.9	68,645	New Jersey	3.9	180,744
Maryland	3.9	119,475	Alaska	3.9	14,873
California	3.8	778,161	North Carolina	3.8	207,254
Georgia	3.8	205,444	Arkansas	3.7	54,463
New York	3.7	390,845	Oregon	3.7	82,817
Texas	3.7	573,433	Colorado	3.6	118,470
Virginia	3.6	164,060	Massachusetts	3.5	143,260
Wisconsin	3.5	114,351	Nevada	3.4	57,858
Washington	3.3	135,243	District of Columbia	3.2	26,079
South Dakota	2.9	15,000			

Note: High-vulnerability workers are those in occupations with top quartile AI exposure and bottom quartile adaptive capacity. National average: 4.0%. Data based on Lightcast county employment (2023) aggregated to state level, using same methodology as MSA geographic analysis.

State-level vulnerability shares range from 5.3% (New Mexico) to 2.9% (South Dakota), with a national average of 4.0%. The states with the largest absolute employment in high-vulnerability occupations are California (778,161 workers), Texas (573,433 workers), and Florida (506,183 workers).

C.8 Demographic Patterns in High-Vulnerability Occupations

Figure 2 presents the demographic composition of high-vulnerability occupations compared to other workers using data from the Survey of Income and Program Participation (SIPP) pooled across 2022–2024. The 6.1 million workers in high-vulnerability roles are disproportionately female (81.3% versus 48.0% in other occupations), reflecting their concentration in clerical and administrative support roles.

Workers in high-vulnerability occupations have substantially lower educational attainment: only 4.9% hold a bachelor's degree or higher, compared to 10.1% in other occupations.

Union membership rates are similar between high-vulnerability (10.1%) and other occupations (11.8%), indicating that collective bargaining coverage does not systematically differ between vulnerable and other occupations. This pattern suggests that union protections may not be concentrated in occupations most exposed to AI-driven displacement.

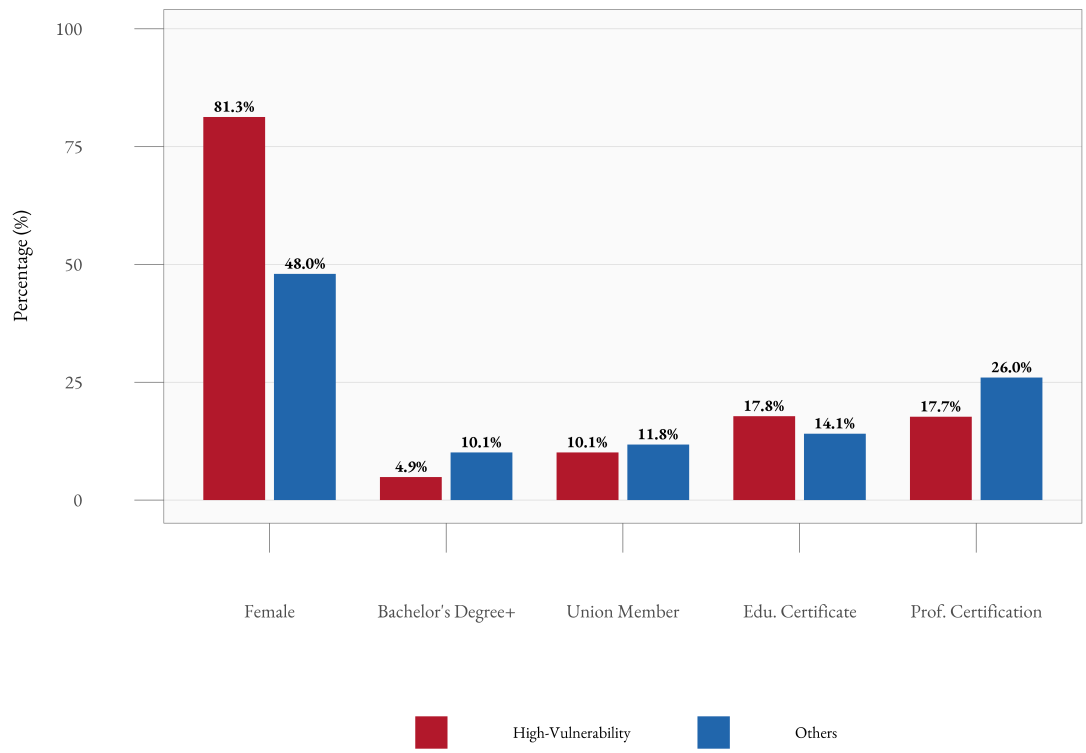

Figure 2: Demographic Composition of High-Vulnerability versus Other Occupations

Notes: High-vulnerability occupations defined as simultaneously in the top quartile of AI exposure and the bottom quartile of adaptive capacity, representing 6.1 million workers. Employment-weighted percentages calculated using baseline adaptive capacity specification. Demographic data from SIPP 2022–2024 pooled. "Bachelor's Degree+" includes bachelor's, master's, professional, and doctoral degrees. "Prof. Certification" refers to professional licenses or certifications (EPROCERT); "Edu. Certificate" refers to educational or vocational certificates (ECERT).

D Robustness Checks

Our main results rest on a composite adaptive capacity index combining four components with equal weights. This section tests the robustness of four key stylized facts across multiple methodological dimensions:

1. **SF1: Positive Correlation** — AI exposure and adaptive capacity are positively correlated ($r \approx 0.502$)
2. **SF2: Prevalence of High Vulnerability** — Approximately 4.2% of the workforce faces

top-quartile AI exposure and bottom-quartile adaptive capacity

3. **SF3: Clerical Concentration** — Vulnerable workers concentrate in clerical and administrative occupations

4. **SF4: Professional-Clerical Gap** — High AI exposure bifurcates into professional (high AC) versus clerical (low AC) groups.[3]

We test these facts across six dimensions of variation:

1. *Transferability measure*: Skills (S), Skills+Work Activities (SW), Skills+Knowledge+Abilities (SKA), all four O∗NET components (SKAW), or skill diversity

2. *Normalization*: L2 (RAW), employment-weighted percentile (EWP), or z-score

3. *Age measure*: Fraction 55+, median age, or vulnerable age brackets

4. *Geographic density*: Included or excluded

5. *Additional components*: Routine task intensity (RTI), routineness z-score, or income[4]

6. *Aggregation method*: Z-score averaging, percentile averaging, or PCA

Each alternative specification represents a methodological choice we could have made differently. The following subsections examine how consequential these choices are for our main findings.

D.1 Alternative Adaptive Capacity Index Specifications

We test alternative specifications that vary transferability measures, age measures, normalization methods, geographic density inclusion, routine task measures, and aggregation methods. Table 8 presents representative specifications spanning these methodological choices.

Across specifications:

[3] Throughout this section, "professional" refers to Management, Business, and Financial Occupations (SIPP codes 10–960) plus Professional and Related Occupations (SIPP codes 1005–3550). "Clerical" refers specifically to Office and Administrative Support Occupations (SIPP codes 5000–5940), which includes secretaries, clerks, administrative assistants, and bookkeepers. Sales occupations are classified separately.

[4] We test specifications adding routine task measures or income. The **routine z-score** following Acemoglu and Autor (2011) standardizes the sum of routine cognitive (Importance of Repeating Same Tasks, Importance of Being Exact or Accurate) and routine manual (Pace Determined by Speed of Equipment, Controlling Machines and Processes, Spend Time Making Repetitive Motions) task content. The **RTI** measure following Autor and Dorn (2013) calculates $\ln(T_R) - \ln(T_M) - \ln(T_A)$ where routine (T_R) averages Importance of Being Exact or Accurate and Finger Dexterity, manual (T_M) uses Multilimb Coordination, and abstract (T_A) averages Organizing, Planning, and Prioritizing Work and Mathematics skill.

Table 8: Representative Adaptive Capacity Specifications

Variant	r	Vuln. (%)	Gap	Overlap (%)
Baseline	**0.50**	**4.2**	**0.54**	**100**
Skills only (S)	0.55	2.5	0.58	90
Full O*NET (SKAW)	0.51	4.4	0.52	100
Skill diversity	0.40	3.3	0.63	60
No density	0.38	5.4	0.53	90
No wealth	0.29	8.0	0.55	90
No age	0.58	0.2	0.56	30
No transferability	0.50	3.1	0.57	60
Median age	0.53	2.3	0.57	80
Vulnerable age	0.50	4.2	0.54	100
+ RTI	0.26	6.1	0.64	100
+ Routine Z	0.52	3.7	0.58	60
Percentile agg.	0.48	4.1	0.56	90
PCA aggregation	0.57	0.1	0.56	10

Representative specifications spanning key methodological choices, including leave-one-out analysis (No density/wealth/age/transferability) and vulnerable age brackets (under 25 or 55+). r = employment-weighted correlation with AI exposure. Vuln. = share of workforce in top quartile AI exposure and bottom quartile AC. Gap = mean AC difference between professional and clerical occupations among high-exposure jobs. Overlap = percentage of high-vulnerability occupations shared with baseline.

- **Correlation with AI exposure**: All 57 specifications show positive correlations ranging from 0.206 to 0.715, with mean 0.501.
- **Professional-clerical gap**: All specifications show positive gaps (0.50–0.70), with high AI exposure occupations bifurcating into professional (high AC) and clerical (low AC) groups.
- **High vulnerability rates**: Range from 0.1% to 8.0%, with baseline at 4.2%. The variation reflects sensitivity to component weighting and threshold definitions.
- **Routine task measures**: RTI correlates positively with AI exposure (r = 0.261) while routine z-score correlates negatively (r = 0.523). High-vulnerability rates differ accordingly: 6.1% under RTI versus 3.7% for routine z-score.
- **Occupation overlap**: Z-score specifications show 30.0–100.0% overlap with baseline high-

vulnerability occupations; PCA shows 10.0% overlap, reflecting its different weighting structure that can assign negative loadings to some components.

PCA-based specifications produce lower correlations because PCA assigns loadings based on variance structure rather than economic theory, sometimes resulting in negative loadings on wealth or transferability. Z-score and percentile methods maintain positive loadings on all components by construction.

D.2 Bootstrap and Robustness Analysis

For the baseline specification, the 95% bootstrap confidence interval (1000 samples) is [0.353, 0.624] with point estimate r = 0.502. All bootstrap samples show positive correlation.

D.2.1 Component Contribution Analysis

The four index components show varying individual correlations with AI exposure: skill transferability (r = 0.227), net liquid wealth (r = 0.591), geographic worker density (r = 0.426), and fraction of workers age 55+ (r = 0.152). All components show positive correlations, with wealth exhibiting the strongest relationship and age the weakest.

Leave-one-out analysis shows that wealth and density make the largest marginal contributions: excluding wealth reduces the correlation by 40%, while excluding density reduces it by 24%. Transferability and age show minimal marginal contributions when other components are present, likely due to intercorrelations. The positive correlation persists across all leave-one-out specifications.

D.2.2 Threshold Sensitivity

Figure 3 shows how high-vulnerability worker counts change across threshold combinations, varying both the AI exposure threshold (columns) and adaptive capacity threshold (rows). Moving from loose thresholds (50th/50th) to strict thresholds (90th/10th) shows gradual transitions in worker counts rather than sharp discontinuities.

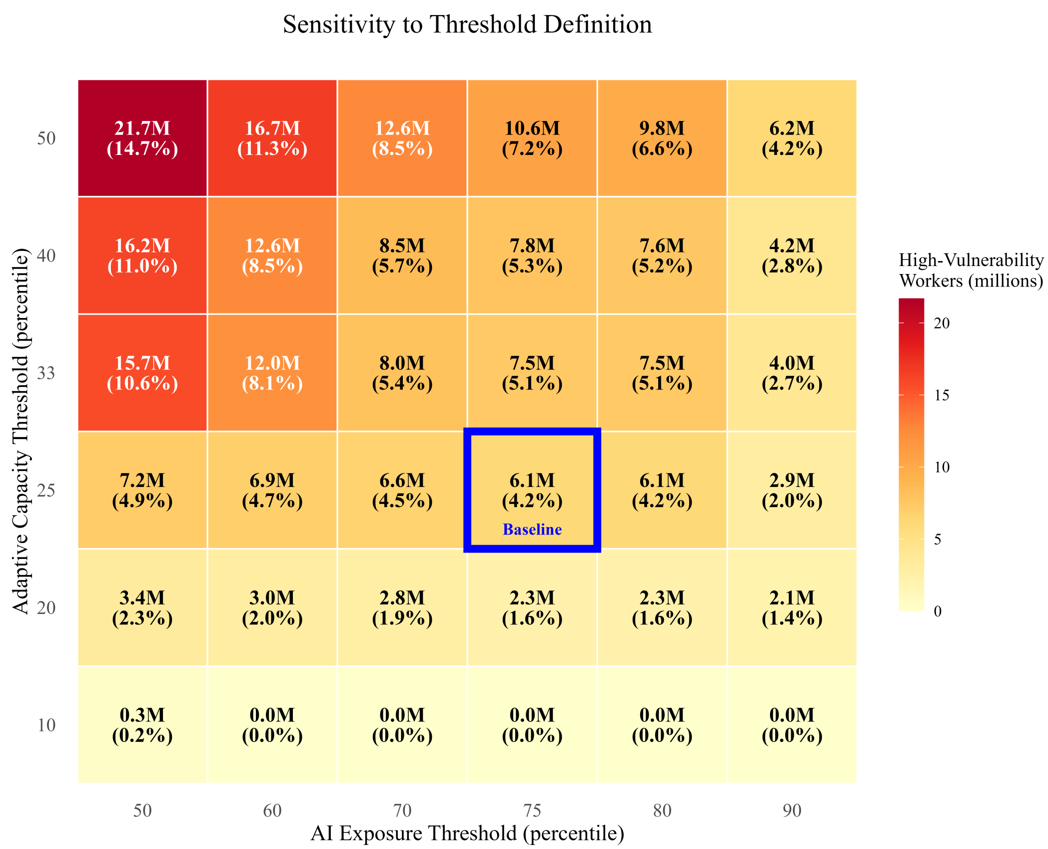

Figure 3: Two-dimensional threshold sensitivity. Each cell shows millions of workers classified as high-vulnerability under that threshold combination (simultaneously AI exposure $\geq$ column percentile and adaptive capacity $\leq$ row percentile). The baseline threshold (75th AI, 25th AC) is outlined in blue. The gradual color gradient indicates smooth sensitivity to threshold choices rather than sharp discontinuities.

D.2.3 Aggregation Level Robustness

The positive correlation holds at multiple levels of aggregation. Figure 4 shows that when aggregating 356 occupations into 10 major groups, the employment-weighted correlation remains positive (r = 0.54). Professional and managerial occupations cluster in the upper-right (high AI exposure, high adaptive capacity), while administrative support occupations cluster in the lower portion. While individual occupation rankings vary across specifications, occupation *types* show greater consistency, with high-vulnerability classifications concentrating in administrative support, customer service, and clerical roles across specifications.

Figure 4: Between-Group Relationship: AI Exposure and Adaptive Capacity by Major Occupation Group. Each point represents a major occupation group, sized by total employment. Employment-weighted correlation r = 0.54.

Figure 5 shows that the positive correlation also holds within individual occupation groups. All 10 major occupation groups exhibit positive within-group correlations between AI exposure and adaptive capacity, with an employment-weighted average of r = 0.48. This within-group pattern suggests that even among occupations in the same broad category, those with higher AI exposure tend to have higher adaptive capacity.

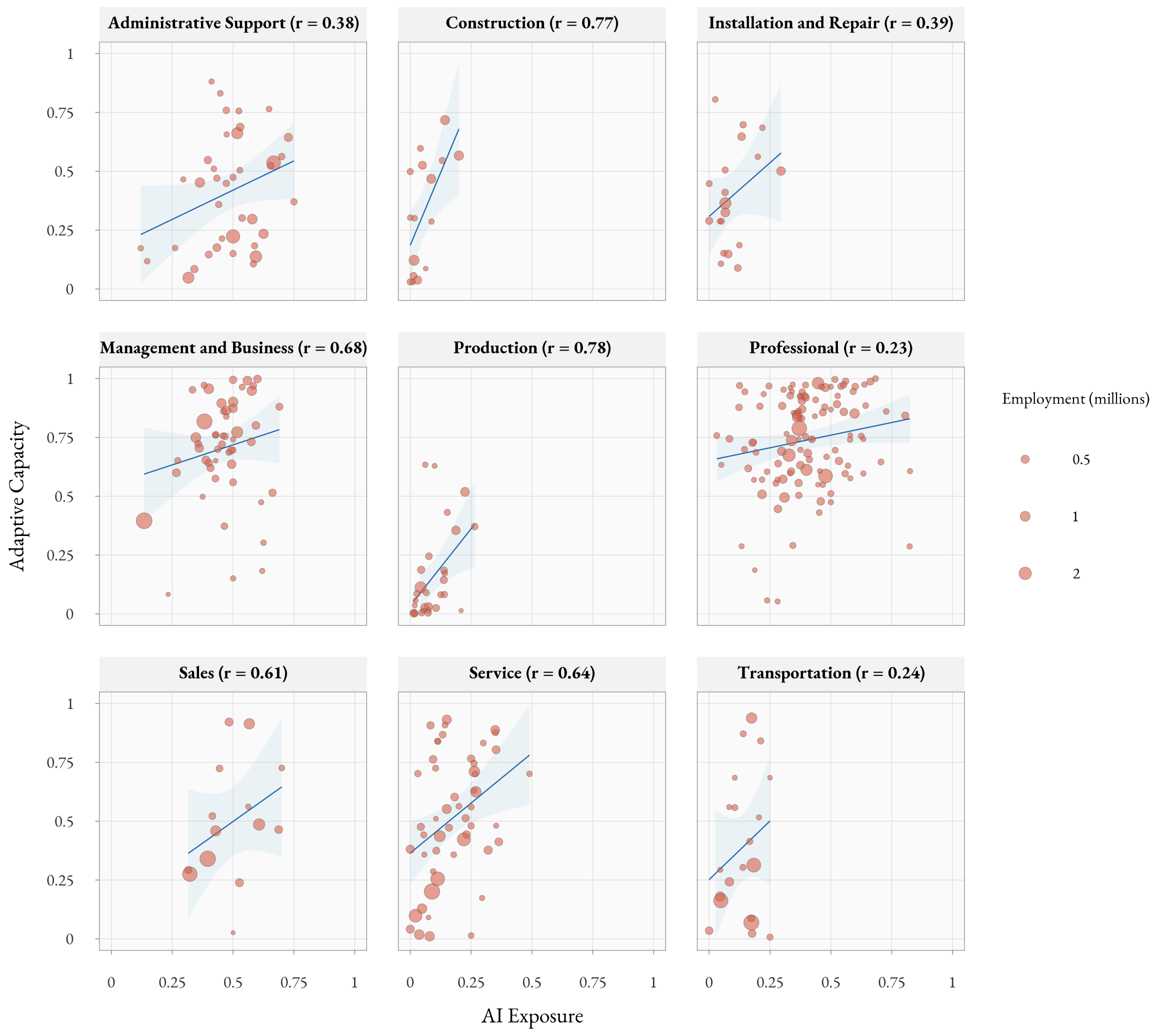

Figure 5: Within-Group Relationship: AI Exposure and Adaptive Capacity Within Each Major Occupation Group. Each panel shows individual occupations within one major group. All 10 groups shown exhibit positive employment-weighted within-group correlations (noted in panel headers). Farming and Fishing is excluded due to insufficient variation (n=4 occupations with 85% of employment in a single occupation).

D.2.4 Monte Carlo Weight Sensitivity

Our baseline assigns equal weights to the four components. To assess sensitivity, we draw 1,000 random weight vectors from Dirichlet distributions: a uniform prior ($\alpha = 1$) and a concentrated prior ($\alpha = 4$). Under both priors, the correlation remains positive. With uniform weights, the mean correlation is 0.408 with 95% of weights yielding correlations between -0.008 and 0.621.

Table 9: Monte Carlo Weight Sensitivity Analysis

	Dirichlet Prior	
Metric	$\alpha = 1$ (Uniform)	$\alpha = 4$ (Concentrated)
Correlation with AI Exposure		
Mean	0.408	0.470
95% CI	[-0.008, 0.621]	[0.253, 0.603]
% Positive	97.4%	100.0%
Stylized Fact Pass Rates		
SF1 ($r > 0.30$)	78.0%	94.6%
SF2 (2–6% vulnerable)	40.7%	52.6%
SF3 (>50% clerical)	83.8%	92.1%
SF4 (gap > 0.2)	100.0%	100.0%
Rank Stability	0.731	0.897

1000 Monte Carlo simulations drawing component weights from Dirichlet($alpha$) distribution. Uniform prior ($alpha = 1$) treats all weight combinations as equally likely. Concentrated prior ($alpha = 4$) centers weights around equal weighting (0.25 each). Rank stability measures consistency of occupation rankings across weight draws (1 = perfectly stable).

D.2.5 Summary

The positive correlation between AI exposure and adaptive capacity, and the professional-clerical divergence among high AI exposure occupations, hold across the specifications tested—at individual occupation, occupation group, and within-group levels. Precise vulnerability counts depend on threshold definitions and aggregation methods, making patterns more reliable than exact percentages.

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