APOLLO

The Impact of AI on the U.S. Labor Market

Early Evidence from Observed Adoption

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Abstract

We examine the wage and employment effects of AI adoption across U.S. occupations using observed usage data from the Anthropic Economic Index rather than the theoretical exposure measures that dominate prior work. Using a difference-in-differences design with occupation and year fixed effects across 321 matched occupations from 2015 to 2025, we find that high-exposure occupations experience a 6.7% decline in real wage growth post-2023 with no detectable employment effects, suggesting firms are capturing AI productivity gains through wage compression rather than workforce reduction. The effect is concentrated among the lowest earners: service workers face a 24.3% decline and the bottom wage quartile a 10.7% decline, while top earners show no significant effect.

Today, 5.8 million workers are affected, but as AI adoption deepens across corporate America, this figure is likely to grow substantially, with significant implications for income inequality and labor market policy in the years ahead.

01 Introduction

Since the release of ChatGPT, researchers, firms, and policymakers have tried to estimate how AI will affect jobs and wages. Early studies projected substantial labor market disruption, but nearly all relied on theoretical AI exposure measures rather than observed AI adoption. The first generation of AI exposure research asked which occupations could be affected by AI using O*NET task descriptions and expert assessments.

AI adoption is accelerating across U.S. firms, yet the distributional consequences for wages and employment remain unknown. Newly available datasets from Anthropic, Microsoft, and Ramp make it possible to measure where AI is actually being used. This shift from potential exposure to realized adoption makes it possible to ask a fundamentally different question: **what is the effect of AI adoption once workers are actually using AI?**

Specifically, we investigate whether high-exposure workers (defined as occupations having an Anthropic Economic Index score ≥0.5) experience significant wage and employment changes compared to low-exposure workers after the release of ChatGPT in late 2022.

This paper makes three contributions to the emerging literature on AI and labor market outcomes. First, we use observed AI usage data, i.e. actual Claude interaction logs, rather than the constructed or theoretical exposure scores that dominate prior work (Felten et al., 2021; Webb, 2019; Brynjolfsson, Mitchell, and Rock, 2018; Eisfeldt et al., 2023).

As illustrated in Figure 1, the existing literature is concentrated in the expert/model quadrant; this paper is among the first to estimate causal labor market effects from the actual usage/realized quadrant, capturing adoption as it is happening rather than as it is projected. Second, it provides early causal evidence via a difference-in-differences design with occupation and year fixed effects of wage compression in high-exposure occupations post-2023, at the moment adoption is visibly scaling.

Third, it produces a conservative lower-bound estimate of aggregate labor income loss ($28 billion annually across 5.8 million workers), grounding an otherwise theoretical debate in a concrete macroeconomic magnitude.

02

Literature Review

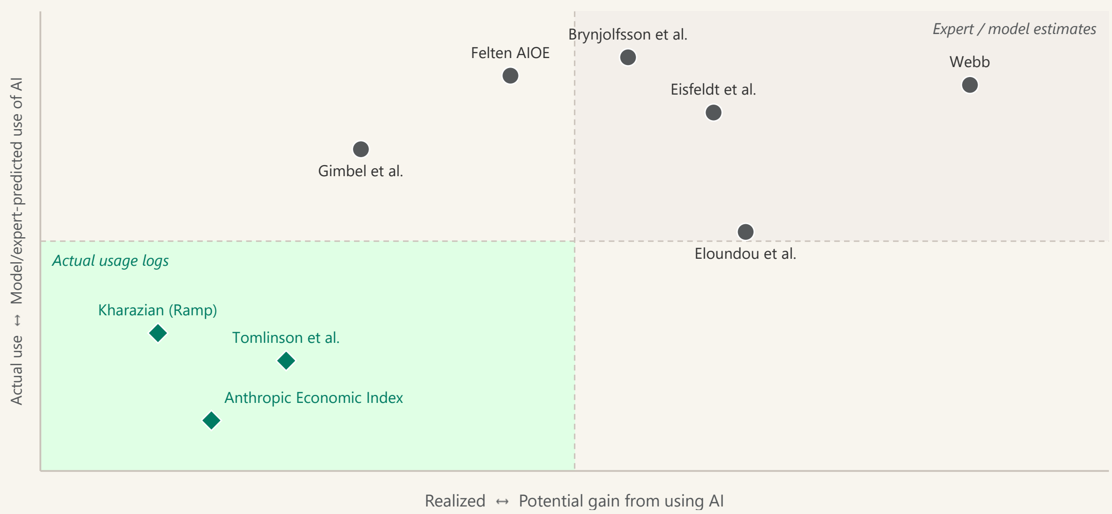
Academic studies on AI exposure and its labor impacts uses the U.S. Department of Labor's Occupational Information Network (O*NET)'s dataset of around 830 occupations. Each occupation has on average 20–30 tasks associated with the role, and the database weights each task based on its importance to the occupational role it is associated with on a scale of 1 (being not important) to 5 (extremely important). This format allows us to understand the extent and importance of the overlap between AI and human work.

The literature analyzing AI exposure has evolved through three stages: (1) theoretical exposure measures based on O*NET, (2) AI-generated exposure ratings, and (3) observed usage measures derived from real-world AI adoption.

We compare five measures that differ in how they define an occupation's exposure to AI. Figure 1 illustrates that as the average of five exposure measures increases, disagreement among different measures also increases, see Figure 2. The biggest difference lies between theoretical measures, which ask the question of what AI could do to a job, and actual usage, which asks what workers in an occupation are actually doing with AI. This difference in framing explains why theoretical measures are higher than actual, as theoretical measures do not take cost of AI use (tokens) into account. Observed usage, while only recently published, has been the most accurate and is the measure that we make use of here.

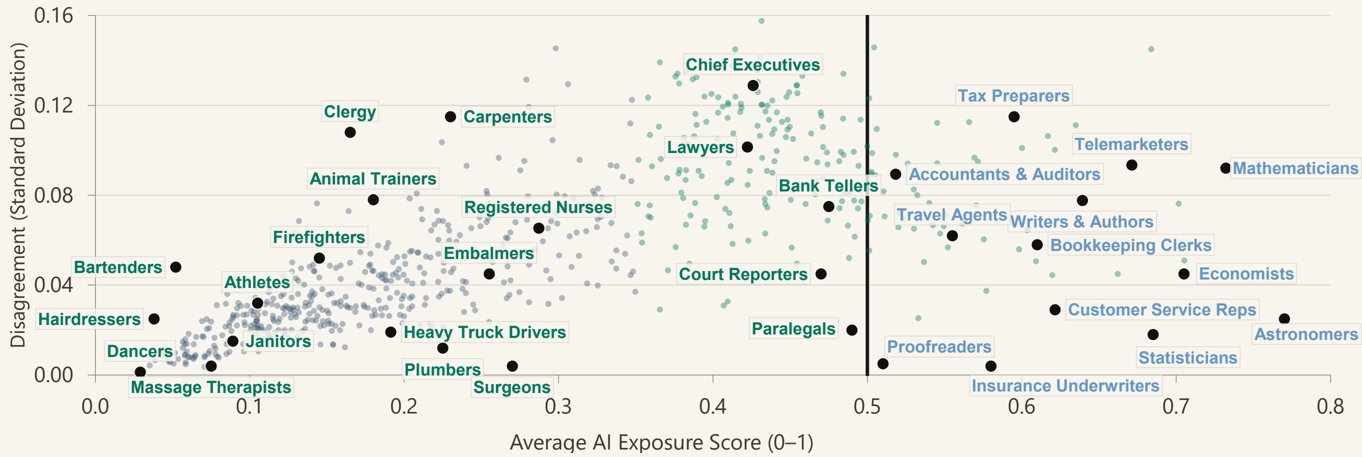
Most recently, Bick et al. (2026) provide the most comprehensive task-level measurement of realized AI adoption to date, using a nationally representative survey linked to detailed O*NET work activities. Their findings directly motivate the approach taken in this paper. They document that genAI adoption is already widespread. Over 80% of occupations and 40% of tasks exhibit adoption rates above 20%. But that existing exposure measures explain only around half of the variation in adoption across workers, with individual-level factors accounting for much of the remainder.

Figure 1: How different studies quantify AI exposure across occupations



1. "O*NET OnLine," accessed June 23, 2026, https://www.onetonline.org/
2. For more information about the literature, see Section I of Appendix A.
3. Bick, Alexander, Adam Blandin, David J. Deming, and Tyler Schumacher. "What Work Does Generative AI Do?" Working Paper, Federal Reserve Bank of St. Louis, Vanderbilt University, and Harvard University, April 2026.
4. Bick, Alexander, Adam Blandin, David J. Deming, and Tyler Schumacher. "What Work Does Generative AI Do?" Working Paper, Federal Reserve Bank of St. Louis, Vanderbilt University, and Harvard University, April 2026.

Figure 2: Studies analyzing the impact of AI on the labor market:
The higher the average estimate of AI exposure, the wider the disagreement



Data as of December 2025. *Note: Includes $27.3bn of investment-grade data center project finance issued by Beignet Investor LLC and backed by Meta. Source: Goldman Sachs

Critically, they find that survey-based measures of realized usage differ systematically from chat log–based measures, including those derived from Anthropic data: chat logs tend to overclassify usage toward generic, activity-based tasks such as editing and programming, while survey-based measures capture the higher-order, purpose-oriented tasks that workers actually associate with their occupations. This distinction has direct implications for interpreting the Anthropic Economic Index used in this paper, which is derived from Claude interaction logs: the exposure scores likely understate the breadth of AI's occupational reach and should be interpreted as a conservative lower bound on realized adoption.

The model in Figure 2 of AI exposure and disagreement (standard deviation) among the five most prominent measures is the one used by the Yale Budget Lab with the addition of the Anthropic usage data. Looking at the graph, it appears that the higher the average exposure, the more deviation there is from the trendline. This pattern of variance being highest at intermediate exposure levels could be due to extremes being easier to classify (for example, it is easy to classify a janitor's work as not being much exposed to AI given the work's physical nature). Further, it could also be that occupations with intermediate scores have more mixed bundles of job tasks, which would mean that exposure methodologies would vary in their classifications.

5. Gimbel, Martha, Molly Kinder, Joshua Kendall, and Maddie Lee. Evaluating the Impact of AI on the Labor Market. Yale Budget Lab, October 2025. https://budgetlab.yale.edu/research/evaluating-impact-ai-labor-market-current-state-affairs
6. A quadratic (parabolic) regression of cross-measure standard deviation on average AI exposure score yields an R^2 of 0.662, compared to 0.578 for a linear fit, suggesting that disagreement among measures is greatest at intermediate exposure levels.

To analyze this further, we ran both T- and F-tests, see Table 1 below. Again, the group defined as low-exposure consists of occupations with an average exposure score less than .5. This test yields a t-statistic of -6.68, which indicates that there is a statistically significant increase in average disagreement in the high exposure group than in the low-exposure group ($p \leq 0.001$). The F-statistic is .699, which is less than 1, indicating that the variance of disagreement is lower within the high-exposure group than within the low-exposure group. This can mean that high-exposure occupations are more uniformly difficult to classify across measures. This difference in variances is statistically significant ($p=0.001$). For more information about the existing literature, see Appendix A.

Table 1:
Disagreement Across AI Exposure Measures: Low vs. High Exposure Groups

Mean SD				
2-3 Group	Mean	Std. Dev.	N	
Low Exposure (score < 0.5)	0.205	0.075	659	
High Exposure (score ≥ 0.5)	0.247	0.090	214	
Two-sample t-test (equal variances)				
Difference	-0.042			t = -6.68***
Variance ratio F-test				
F-statistic				F = 0.699***
(df = 658, 213; p=0.0009)				

***p<0.01. SD is the standard deviation of normalized AI exposure scores across the five measures (Anthropic, Felten, Eisfeldt, Eloundou, Tomlinson), normalized to [0,1] prior to comparison. Groups defined by average normalized exposure score relative to the 0.5 threshold.

03 Data

The U.S. Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) dataset provides information on the wages and employment for 830 occupations, coming from an annual survey of 1.1 million American establishments. The primary outcome variables used in our analysis are annual mean wages (deflated using the CPI-U) and employment counts by occupation.

However, the BLS data excludes small firms, certain military occupations, private household employers, and agriculture. Thus, we use the U.S. Current Population Survey (CPS) which covers around 60,000 households a month to weigh the employment counts from the BLS data. The wider coverage of the CPS data allows this analysis to cover roughly 145 million out of the 170 million workers in the U.S. workforce.

Anthropic's Economic Index, released in March 2026, functions as the observed AI exposure measure here. It covers around 800 occupations matched to the BLS Standard Occupational Classification (SOC) codes. Each occupation has a score of what percent of its tasks have been observed being performed with Anthropic's AI tools, weighted with the importance of tasks in the BLS occupations. Table 2 provides an overview of the data and AI exposure measures used in this analysis.

Table 2:
Descriptive Statistics: Employment, Wages, and AI Exposure by Occupation

	Mean	SD	Min	Max
Panel A: Employment and Real Wages				
Employment 2022	179,118	427,484	330	3,640,040
Employment 2024	186,534	445,656	180	3,988,140
Employment Change (%)	1.54	13.81	-46.88	91.97
Real Wage 2022 ($)	24,657	16,171	9,522	143,946
Real Wage 2024 ($)	24,866	16,119	9,812	143,479
Real Wage Change (%)	0.36	6.06	-52.08	33.00
Panel B: AI Exposure Measures				
Anthropic Economic Index	0.171	0.156	0.000	0.745
Felten et al. (AIOE, z-score)	-0.019	1.010	-2.112	1.528
Eisfeldt et al.	0.222	0.206	0.000	0.958
Eloundou et al. (GPTs are GPTs)	0.326	0.220	0.000	1.000
Tomlinson et al. (Copilot)	0.159	0.098	0.000	0.492
Panel C: Cross-measure correlations				
Anthropic × Felten	0.545			
Anthropic × Eisfeldt	0.626			
Anthropic × Eloundou	0.649			
Anthropic × Tomlinson	0.549			
Felten × Eisfeldt	0.776			
Felten × Eloundou	0.848			
Felten × Tomlinson	0.690			
Eisfeldt × Eloundou	0.869			
Eisfeldt × Tomlinson	0.664			
Eloundou × Tomlinson	0.706			
Occupations (Panel A)	321			
Occupations (Panel B)	321 (Anthropic); up to 798 (others)			

Notes: Employment and real wage data from BLS Occupational Employment and Wage Statistics (OEWS), 2022 and 2024. Real wages deflated using BLS CPI-U (all-urban consumers, base 1982–84). Panel A sample restricted to 321 occupations matched across BLS OEWS and Anthropic Economic Index via 6-digit SOC code. Panel B reports summary statistics across all available occupations per measure. Felten et al. reported as original z-score; all other measures normalized to 0–1. Panel C reports pairwise Pearson correlations; all significant at p<0.001.

Sources: BLS OEWS 2022 and 2024; Anthropic Economic Index (Massenkoff and McCrory, 2026); Felten et al. (2021); Eisfeldt et al. (2023); Eloundou et al. (2024); Tomlinson et al. (2025).

04 Methodology

We use a Differences-in-Differences (DiD) model to analyze the impact of AI adoption on employment and wages for each occupation. High exposure occupations are defined as ones with an Anthropic Economic Index score greater than or equal to 0.5 that have been matched with occupations in the BLS and CPS data. The structural break is in 2023, the first year in which ChatGPT was available for public use. We further break down this analysis into occupation size tercile, wage quartile, and occupation type to understand which groups bear the impact of wage and employment changes.

The DiD regression includes year and occupation fixed effects, and the standard errors are clustered at the occupation level. The DiD regression is run two times, one for wage effects (Equation 1), and the next for the employment effects (Equation 2). Appendix A contains more detail on the methods employed including the event studies for each regression.

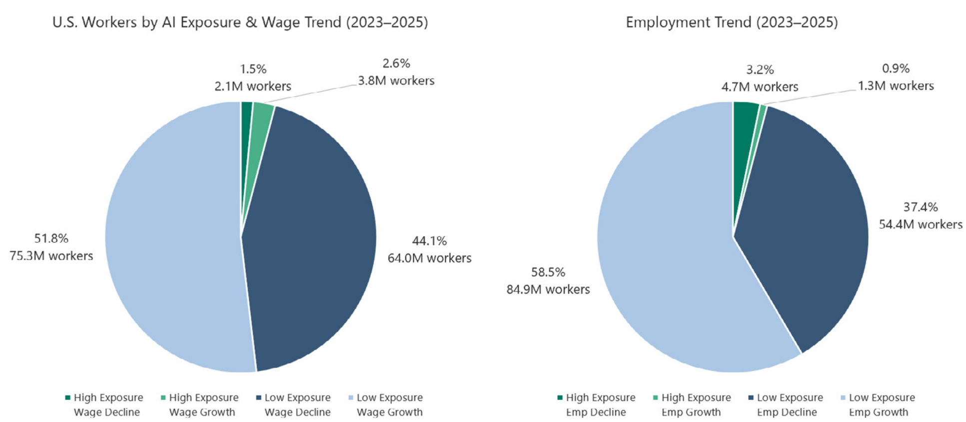
$$\log(RealWage_{it}) = \alpha + \beta(Post_t \times AnthropicExposure_i) + \gamma_i + \delta_t + \varepsilon_{it}$$

$$\log(Employment_{it}) = \alpha + \beta(Post_t \times AnthropicExposure_i) + \gamma_i + \delta_t + \varepsilon_{it}$$

05 Results

This analysis first yields descriptive analytics: 5.8 million workers in the U.S. are currently working in high exposure occupations (as defined above), which represents about 3.7% of the U.S. labor force, see Figure 3. This number is significantly lower than theoretical estimates have projected over the past three years.

Figure 3: AI Exposure Breakdown of Labor Force



7. See Appendix A for more information on the Difference-in-Differences model

Overall, workers who are in high-exposure occupations saw their wages grow about 6.7 percentage points slower than workers not in high-exposure occupations after 2023 (see Table 3). This finding is statistically significant, and it takes into account the underlying differences between occupations and annual trends in the labor market. As shown in the regression results in Table 3, no significant employment effect was found from an occupation having a high AI exposure score.

Standard errors clustered by occupation. Occupation and year fixed effects included.

Sample: BLS OEWS 2015–2025. High exposure defined as Anthropic score ≥ 0.5.

The AI Exposure Score level term is absorbed by occupation fixed effects and is omitted from the table.

^* p<0.1, ^(**) p<0.05, ^(***) p<0.01

When broken down into demographic groups (see Table 4, Table 5, and Figure 4), it becomes clear that workers in the bottom quartile of the wage distribution had their real wage growth decline by around 10.7% relative to low-exposure occupations, compared to 5.4% in the second quartile and 4.0% in the third quartile. The top quartile showed no statistically significant wage effect, which may suggest high earners are better positioned to absorb or benefit from AI adoption. Service occupations (such as childcare workers, concierges, waiters, police officers, social workers, and others) had their real wage growth fall by about 24.3% relative to low-exposure occupations after 2023. The service occupation estimate (-24.3%) is based on a small subsample (n=239 occupation-year observations) and may be sensitive to the composition of high-exposure occupations within that group. This result should be interpreted with caution. Management and professional occupations (such as top executives, financial managers, and administrators) also had significant impacts on their real wage growth, as it fell 4.1% relative to non-exposure peers. Blue-collar workers showed no statistically significant effects, which could suggest that AI has had limited reach into more physically intensive work. The wage growth effect is the strongest in smaller occupations (ones with fewer total people employed). This could show that more specialized roles are more exposed to AI adoption, and larger occupations have more task variety that could buffer the impact.

To confirm that these findings are not sensitive to the choice of exposure threshold, we conduct a robustness check re-estimating the main specifications at cutoffs of 0.4 and 0.6, with results reported in Table 6 in Appendix A.

Table 3:
Main Difference-in-Differences Results

	(1)	(2)
	log(Employment)	log(Real Wage)
AI Exposure × Post	-0.0639	-0.0667^(***)
	(0.0870)	(0.0181)
Constant	11.1585^(***)	10.0931^(***)
	(0.0043)	(0.0009)
Observations	3,296	3,296
Adj. R^2	0.991	0.989

Table 4:
Heterogeneity by Pre-Period Wage Quartile

	log(Employment)				log(Real Wage)			
2-5(lr)6-9	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Q1 (Low)	Q2	Q3	Q4 (High)	Q1 (Low)	Q2	Q3	Q4 (High)
AI Exposure × Post	0.0024	-0.5262^(**)	0.0699	-0.0869	-0.1073^(***)	-0.0570	-0.0405^*	-0.0284
	(0.1597)	(0.2536)	(0.1381)	(0.1157)	(0.0311)	(0.0434)	(0.0229)	(0.0276)
Observations	559	645	902	1,190	559	645	902	1,190

Coefficient on interaction term AI Exposure × Post shown.

Wage quartiles defined using pre-period (2015–2022) mean occupation wage.

Standard errors clustered by occupation.

* p<0.1, ^(**) p<0.05, ^(***) p<0.01

Table 5:
Heterogeneity by Occupation Group

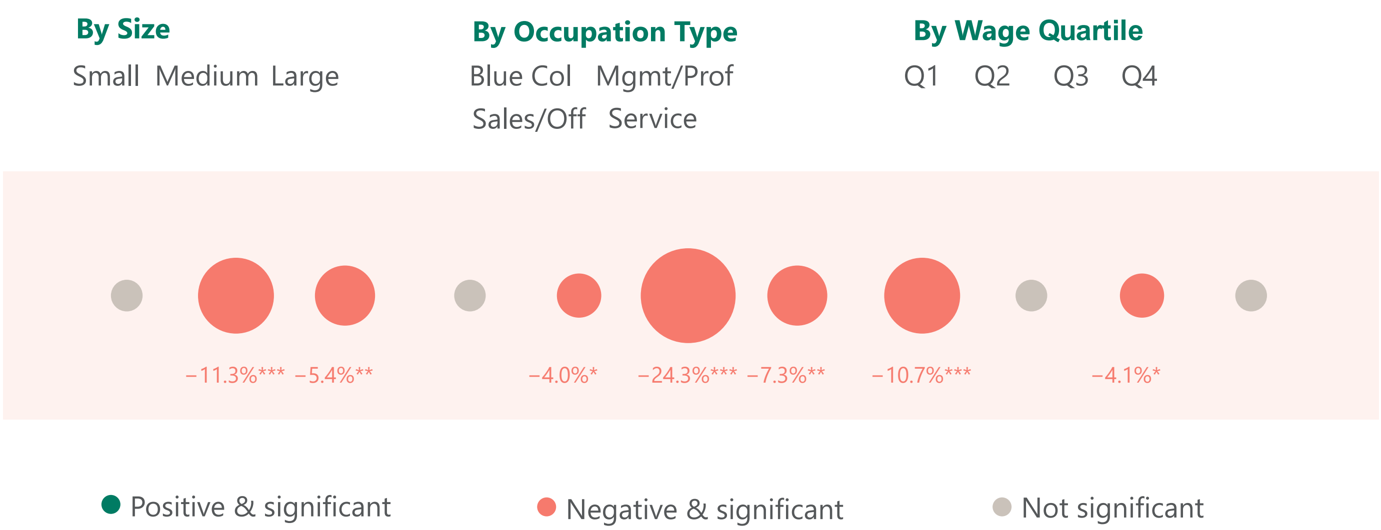
	log(Employment)				log(Real Wage)			
2-5(lr)6-9	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Mgmt/Prof	Service	Sales/Office	Blue Collar	Mgmt/Prof	Service	Sales/Office	Blue Collar
AI Exposure × Post	-0.0014	-0.3214^(**)	-0.0612	2.0186	-0.0395^*	-0.2432^(***)	-0.0730^(**)	-0.3799
	(0.0926)	(0.1157)	(0.1967)	(1.3865)	(0.0212)	(0.0361)	(0.0344)	(0.2361)
Observations	2,035	239	627	395	2,035	239	627	395

Occupation groups defined by 2-digit SOC code.

Standard errors clustered by occupation.

^* p<0.1, ^(**) p<0.05, ^(***) p<0.01

Figure 4: Who is experiencing an impact on wages of AI exposure?



06

Net Macroeconomic Impact

Some 5.8 million U.S. workers, roughly 3.7% of the labor force, are currently employed in high-exposure occupations and bearing some wage costs of AI adoption. This number forms a lower bound for the scope of AI's labor market impact, as it excludes workers in complementary occupations who may also be affected, as well as any employment growth within exposed occupations themselves. Looking ahead, the BLS projects the high-exposure workforce will grow to 5.9 million by 2032, meaning the population of affected workers will expand even as wages within it continue to compress. As AI adoption deepens across corporate America, the true number of workers feeling these effects could grow substantially beyond what current exposure measures capture.

07

Discussion

The evidence suggests that the first measurable labor market effect of AI adoption has been wage compression rather than employment displacement, with the burden falling disproportionately on the least economically secure workers. Today, 5.8 million workers in high-exposure occupations are feeling these effects, but this figure almost certainly understates what is coming in the future. AI adoption across corporate America remains in its early stages, and as firms integrate these tools more deeply into their workflows, more occupations will cross the threshold into high exposure. The workers affected today are best understood as the leading edge of a much larger adjustment, with potentially profound implications for income inequality and living standards, particularly for lower-wage workers who have the fewest resources to weather the transition.

Several limitations should be noted. The exposure measure is specific to Anthropic, the only AI provider to have released usage data for public research, meaning AI exposure per occupation is likely understated. Only 321 of roughly 800 BLS occupations were matched, and the post-2023 period may be partially confounded by post-pandemic labor market dynamics. The contribution of this paper is therefore not only its estimates of wage effects, but its demonstration that AI research has entered a new phase, one in which labor market impacts can be measured from observed adoption rather than predicted from theoretical exposure. The 5.8 million workers affected today are a harbinger. The critical policy question is not whether AI will reshape the labor market more broadly, but how quickly, and whether workers will have the support they need when it does.

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Appendix A

1.Literature Review

Theoretical measures form the first group in the literature, and they are aimed at predicting AI exposure for a given occupation from task and ability descriptions rather than observed usage. Michael Webb's "The Impact of Artificial Intelligence on the Labor Market," published in 2019, was the first to systematically map O*NET task descriptions onto AI and robotics patent language, establishing the methodological precedent for studies that followed—though subsequent work has questioned the reliability of his estimates. Building on this foundation, Felten, Raj, and Seamans developed the AI Occupational Exposure (AIOE) Index, also grounded in O*NET. Rather than task descriptions, they map 10 AI application areas onto O*NET ability scores, producing an index that expresses each occupation's exposure relative to the mean. More recent studies have relied on the work of Eloundou et al. (2024), which had GPT-4 rate each O*NET task for its susceptibility to LLM assistance, aggregating task-level ratings to the occupation level to produce an exposure score. Eisfeldt et al. (2023) take a different approach: rather than using O*NET directly, they construct their measure from occupational descriptions on O*NET combined with job postings data, using text embeddings to estimate the semantic similarity between each occupation and a set of AI-related skills and technologies. Brynjolfsson, Mitchell, and Rock (2018) take yet another approach, using a structured rubric of questions to score each occupation on its suitability for machine learning, producing a constructed expert assessment of potential exposure. Webb (2019) sits furthest in the constructed/potential quadrant of the literature, as his scores derive entirely from NLP overlap between patent texts and O*NET task descriptions with no human judgment involved.

More recently, realized usage measures have emerged from AI platforms such as Anthropic, offering an empirical alternative to theoretical prediction. Rather than inferring exposure from task descriptions or ability scores, these measures use actual model usage data to assess how deeply AI has penetrated occupational workflows. Tomlinson et al. (2025) draw on Microsoft Copilot interaction data to assign each occupation an AI applicability score across its constituent work activities. Massenkoff and McCrory (2026) take a similar approach using Anthropic's Claude usage logs, estimating the share of occupational tasks—weighted by their relative importance—that are being performed with AI assistance, which is the measure underlying the Anthropic Economic Index used in this paper. Kharazian et al. (2025) similarly use observed enterprise spending data from Ramp to construct an occupation-level measure of realized AI adoption. Compared to the theoretical measures, the realized usage measures found substantially lower AI exposure for almost every occupation (see Figure 5). Gimbel et al. (2025) examine disagreement across these measures directly, documenting that occupations rank very differently depending on whether exposure is defined theoretically or by observed usage.

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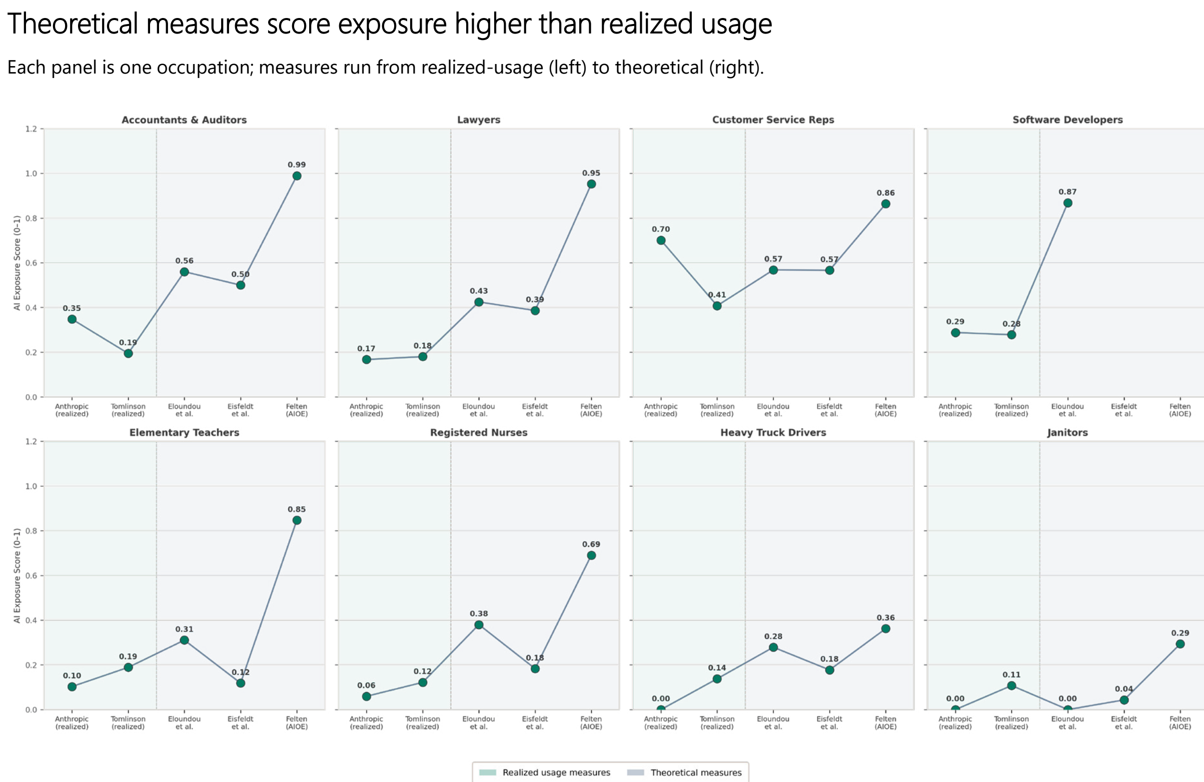
13. Brynjolfsson, Erik, Tom Mitchell, and Daniel Rock. "What Can Machines Learn, and What Does It Mean for Occupations and the Economy?" AEA Papers and Proceedings 108 (2018): 43–47.

Figure 5: Actual versus Theoretical AI Exposure Measures



While not publicly released for individual analysis, market- and firm-level measures of AI exposure are beginning to emerge. Goldman Sachs recently constructed a basket of AI-exposed firms by overlaying task-level AI capability estimates onto firm-level labor cost ratios, effectively translating occupation-level exposure into an investable metric. PwC's 2026 AI Jobs Barometer takes a broader approach, analyzing over one billion job postings across six continents to identify a bifurcated labor market: "professionalized" roles where AI complements human expertise are seeing twice the job growth and significantly faster wage growth relative to "democratized" roles where AI lowers the skill threshold for entry. Together, these firm- and market-level approaches suggest that occupation-level exposure measures have practical salience beyond academic measurement—a motivation for the empirical analysis that follows.

14. Tomlinson, Kiran, Sonia Jaffe, Will Wang, Scott Counts, and Siddharth Suri. "Working with AI: Measuring the Applicability of Generative AI to Occupations." arXiv:2507.07935, December 2025. https://doi.org/10.48550/arXiv.2507.07935.
15. Massenkoff, Maxim, and Peter McCrory. "Labor Market Impacts of AI: A New Measure and Early Evidence." March 5, 2026. https://www.anthropic.com/research/labor-market-impacts.
16. Kharazian, Ara, Lisa Simon, and Ryan Stevens. "A New Look at AI's Impact on Jobs." Ramp, 2025. https://ramp.com/data/ai-jobs-impact.
17. Gimbel, Martha, Molly Kinder, Joshua Kendall, and Maddie Lee. Evaluating the Impact of AI on the Labor Market. Yale Budget Lab, October 2025. https://budgetlab.yale.edu/research/evaluating-impact-ai-labor-market-current-state-affairs.
18. Goldman Sachs Global Investment Research, "The Potentially Large Effects of Artificial Intelligence on Economic Growth," March 2023.
19. Brown, Peter, and Joe Atkinson. 2026 Global AI Jobs Barometer. PwC, 2026. https://www.pwc.com/gx/en/services/ai/ai-jobs-barometer.html.

2. Data

SOC Crosswalk & Merging Process

Each dataset used (Anthropic, BLS, CPS) contained Standard Occupational Classification (SOC) codes to identify each unique one. The BLS data covers around 800 occupations at the 6-digit SOC level. The Anthropic Economic Index also covers around 800 occupations at the 6-digit SOC level. The Current Population Survey (CPS) data, however, uses its own occupation coding system that does not map 1:1 to the SOC code system.

To mitigate this mismatch, we first matched the BLS OEWS to the Anthropic Index directly through using the 6-digit SOC code, which resulted in 321 matched occupations, as not every BLS occupation had one logged in the Anthropic data. The occupations without Anthropic Index scores are largely ones with small sample sizes, and Anthropic excludes them in efforts to protect data privacy. These excluded occupations will be ones that are more niche and rare, so the dataset used here is not systematically missing a whole sector. Second, we used the BLS NEM-SOC-CPS crosswalk to link the CPS occupation codes to SOC codes so we could pull the CPS employment weights for the matched occupations.

CPS Weighting Procedure

The BLS OEWS employment data undercounts the full workforce, as it only covers around 77 million out of the 170 million workers in the U.S. workforce. The BLS data does not include small firms, self-employed, agriculture, etc. CPS by contrast covers more of the workforce, so to create the employment figures, the CPS data was essential. For each occupation in the sample, we took the CPS employment count and used it as a weight to adjust the OEWS figures when computing aggregate estimates. Using the CPS data allows for a more representative employment count. The wage regressions, however, use the raw OEWS data, as they do not rely on relative size of occupations, which would require the CPS data.

Variable Construction

To get the real wages for each occupation, we deflated the BLS OEWS annual mean wage using the BLS CPI-U, all-urban consumers (not seasonally adjusted) with the base period of 1982–1984. This procedure was applied for each observation from 2015–2025. Otherwise, almost all occupations showed an increase in nominal wages.

High exposure occupations were defined using a binary variable if an occupation's Anthropic Economic Index score was greater than or equal to 0.5, meaning that at least half of an occupation's tasks (weighted by importance) have been observed being done with AI assistance. We follow PwC in using 0.5 as the threshold for high exposure. Of the 321 occupations that met the merging criteria, 11 are defined as high exposure (see Appendix B).

The indicator for the post period was a binary variable that was 1 for years 2023–2025 and 0 for the years 2015–2022. The break is in 2023 because it marks the first full year in which ChatGPT was publicly available. The interaction of high exposure and the post period is the DiD treatment variable (which has a coefficient of -0.0667 in Table 3).

3. Methodology

Again, the equations for the Difference-in-Differences model are shown below, along with the event studies associated with each. Each regression includes year and occupation fixed effects. Occupation fixed effects absorb all time-invariant differences across occupations—such as baseline skill requirements, industry composition, or long-run wage levels—so that the identifying variation comes only from changes within an occupation over time. Year fixed effects absorb economy-wide shocks common to all occupations in a given year, such as macroeconomic conditions, inflation, or aggregate labor market trends, ensuring that the AI Exposure × Post coefficient is not confounded by broader shifts unrelated to AI adoption. No additional occupation-level controls (such as education requirements or industry) are included beyond the fixed effects, since occupation fixed effects already absorb any characteristic of an occupation that does not vary over the sample period; time-varying controls were not included in the baseline specification in order to avoid conditioning on variables that could themselves be affected by AI adoption (a "bad controls" problem). Standard errors are clustered at the occupation level throughout to account for serial correlation in outcomes within an occupation across years.

$$\log(\text{RealWage}_{it}) = \alpha + \beta\,(\text{Post}_t \times \text{AnthropicExposure}_i) + \gamma_i + \delta_t + \varepsilon_{it}$$

$$\log(\text{Employment}_{it}) = \alpha + \beta\,(\text{Post}_t \times \text{AnthropicExposure}_i) + \gamma_i + \delta_t + \varepsilon_{it}$$

20. Tomlinson, Kiran, Sonia Jaffe, Will Wang, Scott Counts, and Siddharth Suri. "Working with AI: Measuring the Applicability of Generative AI to Occupations." arXiv:2507.07935, December 2025. https://doi.org/10.48550/arXiv.2507.07935.

Figure 6: Event Study: AI Exposure × Year (Real Wage)

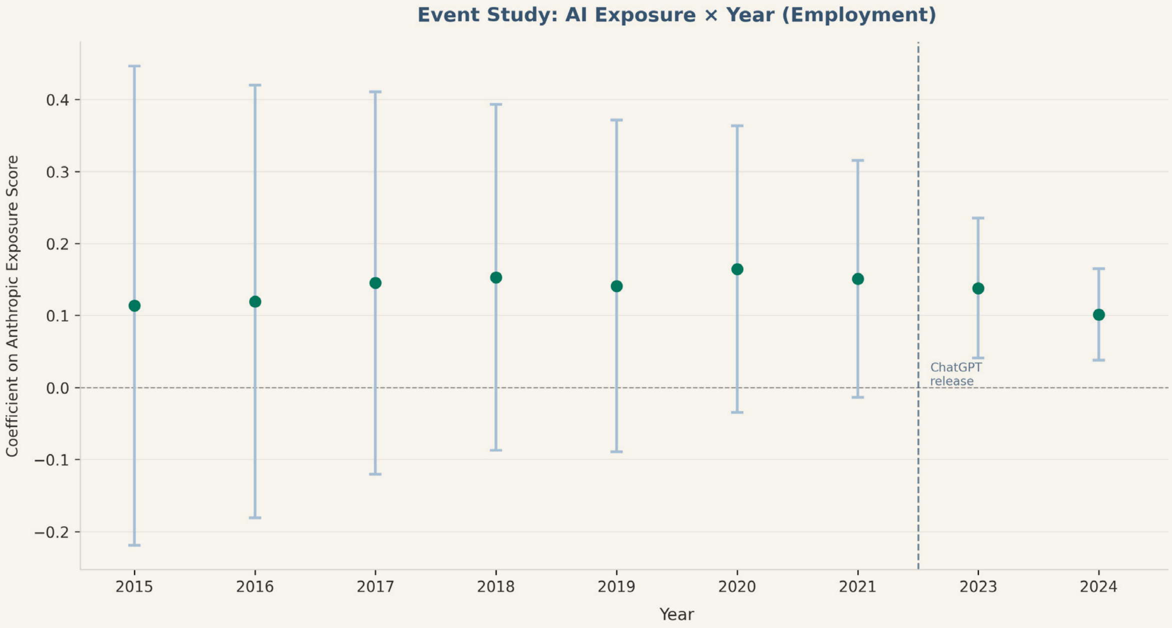
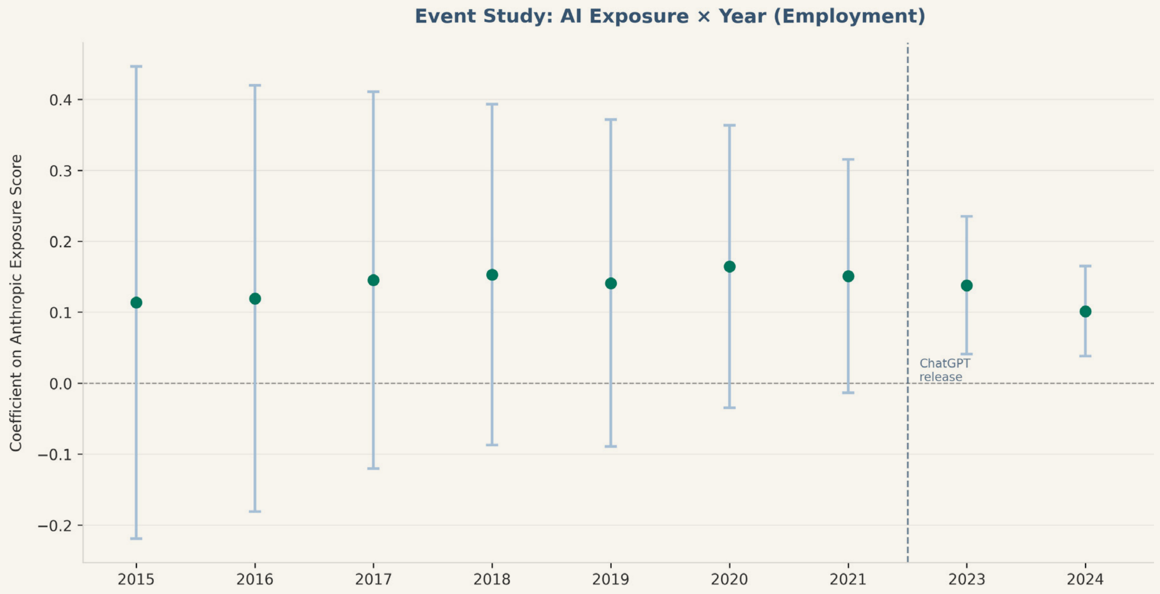


Figure 7: Event Study: AI Exposure × Year (Employment)



To break the regression results down by wage, occupation size, and sector, we re-ran each regression separately for each subgroup. The regression is re-estimated separately for each subgroup with the same fixed effects and standard errors clustered at the occupation level. Thus, β captures the within-group treatment effect of AI exposure.

The Net Macroeconomic Impact section calculates the aggregate labor income loss due to AI labor impacts using Equation 3 across high exposure occupations.

$$\text{Income Loss} = \sum_i (\text{real wage effect}_i \times \text{CPS employment count}_i \times \text{mean wage}_i)$$

4. Results

The size of the highly exposed workforce of 5.8 million workers came from the CPS employment counts across all the occupations with an Anthropic Economic Index score greater than or equal to 0.5. We then divided this by the total CPS-weighted workforce of around 145 million to get the 3.7% share of the total labor force. To reiterate, this sum of exposed workers uses the CPS and not the BLS OEWS counts. Projecting this forward, we used the BLS Employment Projections Program that uses 2022 as the base year and projects out to 2032. We merged the BLS 2032 projected employment figures onto the matched occupation list using the SOC code. We then applied the same Anthropic score cutoff of 0.5 to find the number of high exposure occupations and headcounts to get to 5.9 million people. This holds the exposure threshold and assignments fixed, so it assumes the same occupations remain high exposure in 2032, which is a simplification used in this model.

Table 6 presents the check for robustness with different cutoffs for the definition of a "high-exposure" occupation.

For the wage outcomes, the negative effect holds across all three cutoffs, with the coefficient remaining statistically significant at the 0.4 threshold (-1.89%, p≤0.05) and negative but insignificant at the 0.6 threshold (-1.74%), likely reflecting the very small number of occupations above that level. The baseline result of -6.7% at the 0.5 cutoff sits between these estimates, consistent with a gradient in which stricter definitions of high exposure capture a more intensely affected group. For employment, no cutoff yields a statistically significant effect, confirming that the null employment result is not a result of the chosen threshold. Together, these results suggest that the core findings are robust to reasonable variation in the exposure cutoff.

The occupation examples in the results text are illustrative examples drawn from the occupations within each SOC category in the regression sample. They are not separately reported point estimates. Appendix B includes exposure, real wage, and employment changes for each of the 321 matched occupations.

Table 6:
Robustness: Alternative High-Exposure Cutoffs

	(1)	(2)	(3)
	Baseline (≥0.5)	Alt. Cutoff (≥0.4)	Alt. Cutoff (≥0.6)
Panel A: log(Real Wage)			
AI Exposure × Post	–0.0667***	–0.0189***	-0.0174
	(0.0181)	(0.00798)	(0.0143)
Panel B: log(Employment)			
AI Exposure × Post	–0.0639	–0.0279	-0.0715
	(0.0870)	(0.0452)	(0.0812)
Observations	3,296	3,296	3,296
Occupation FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Standard errors clustered by occupation in parentheses.

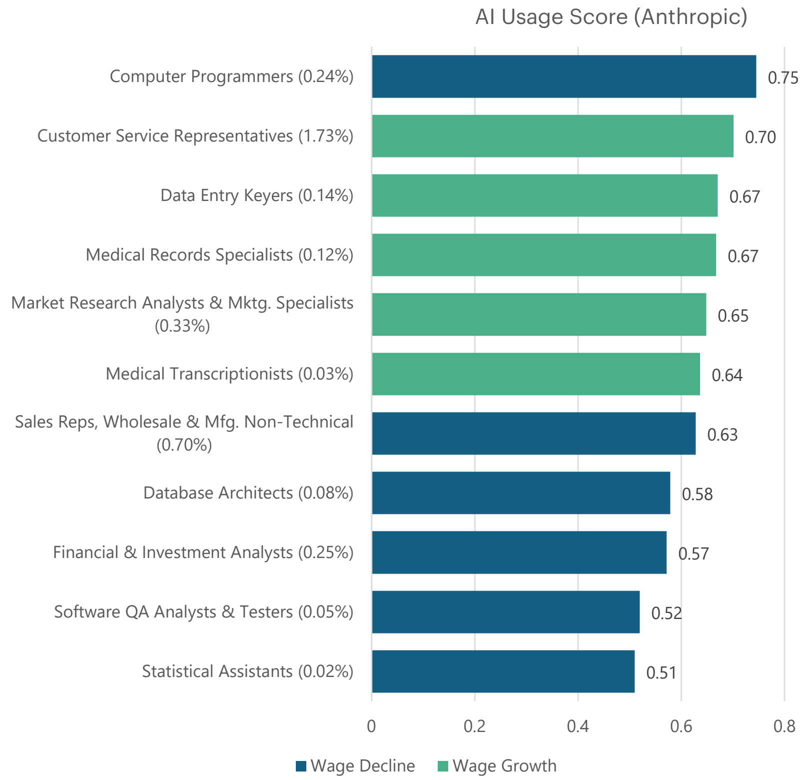
* p<0.1, ** p<0.05, *** p<0.01

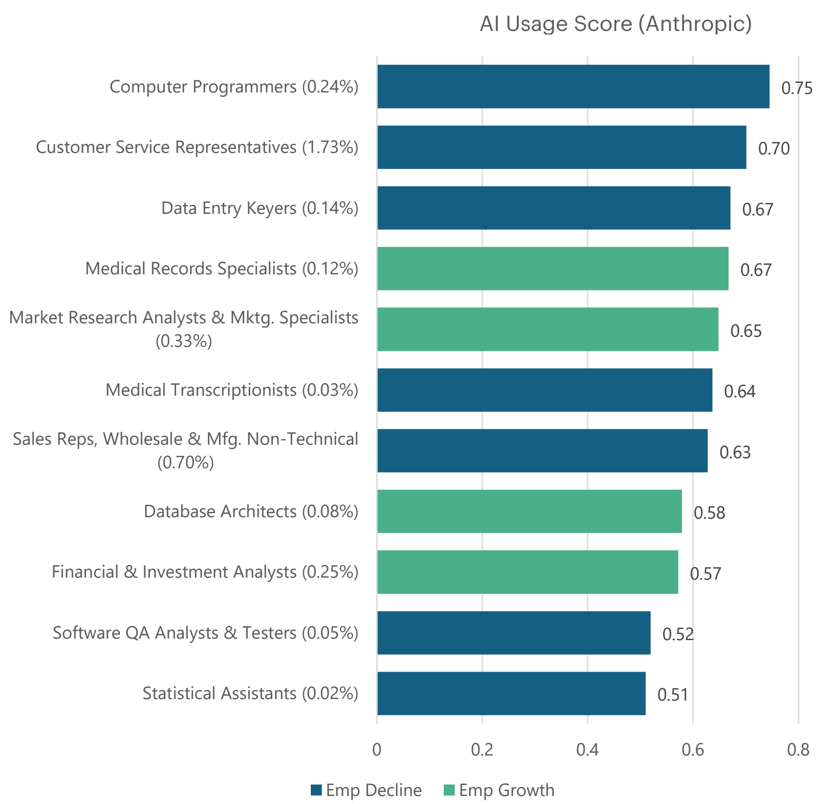
High exposure defined as Anthropic Economic Index score ≥ threshold value. Baseline follows PwC (2026) in using 0.5.

21. US Bureau of Labor Statistics, Employment Projections, 2022-2032, US Department of Labor, 2023: https://www.bls.gov/emp/

Figure 8: High-Exposure Occupations

3.7% of Workers (6 million) Are in High-Usage Occupations





Appendix B

Employment and Real Wage Changes by Occupation, 2022–2024

Sources: BLS OEWS 2022 and 2024; Anthropic Economic Index (Massenkoff and McCrory, 2026).

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
Table B1 continued					
SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
-1251	Computer Programmers	0.75		-17.2	-6.1
43-4051	Customer Service Representatives	0.70		-5.3	2.6
43-9021	Data Entry Keyers	0.67		-14.0	3.2
29-2072	Medical Records Specialists	0.67		0.1	2.1
13-1161	Market Research Analysts and Marketing Specialists	0.65		7.8	2.1
31-9094	Medical Transcriptionists	0.64		-11.5	-1.5
41-4012	Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products	0.63		-0.5	-1.3
15-1243	Database Architects	0.58		3.7	-2.7
13-2051	Financial and Investment Analysts	0.57		16.9	-0.2
15-1253	Software Quality Assurance Analysts and Testers	0.52		1.7	-2.9
43-9111	Statistical Assistants	0.51		-12.1	-5.4
15-1212	Information Security Analysts	0.49	—	9.6	-0.7
15-1254	Web Developers	0.48	—	-11.0	5.1
15-2099	Mathematical Science Occupations, All Other	0.48	—	21.4	-4.0
27-3042	Technical Writers	0.47	—	14.2	-0.9
15-1232	Computer User Support Specialists	0.47	—	0.1	-1.7
43-9031	Desktop Publishers	0.46	—	-39.0	5.1
15-2051	Data Scientists	0.46	—	46.2	0.7
27-3031	Public Relations Specialists	0.45	—	6.0	-4.7
43-6014	Secretaries and Administrative Assistants, Except Legal, Medical and Executive	0.45	—	-4.9	2.2
19-3094	Political Scientists	0.45	—	5.1	1.6
43-9061	Office Clerks, General	0.45	—	-0.3	3.0
41-3031	Securities, Commodities and Financial Services Sales Agents	0.44	—	6.6	2.1
19-4061	Social Science Research Assistants	0.44	—	14.7	2.5
43-4171	Receptionists and Information Clerks	0.43	—	-4.6	3.6
19-3022	Survey Researchers	0.43	—	-2.0	3.0
25-1022	Mathematical Science Teachers, Postsecondary	0.43	—	4.9	-4.0

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
27-3091	Interpreters and Translators	0.43	—	2.3	-2.0
15-2031	Operations Research Analysts	0.43	—	2.6	-3.6
15-2021	Mathematicians	0.42	—	7.2	0.2
25-4012	Curators	0.41	—	5.7	-3.3
25-3041	Tutors	0.41	—	-0.2	-0.7
41-3041	Travel Agents	0.41	—	11.2	1.7
43-4161	Human Resources Assistants, Except Payroll and Timekeeping	0.40	—	-10.7	1.2
13-1071	Human Resources Specialists	0.40	—	9.8	1.6
43-2011	Switchboard Operators, Including Answering Service	0.39	—	-24.7	5.4
43-4111	Interviewers, Except Eligibility and Loan	0.39	—	-6.7	2.8
19-2011	Astronomers	0.38	—	-27.8	-1.7
19-3041	Sociologists	0.38	—	-1.0	2.7
27-1024	Graphic Designers	0.37	—	1.1	-0.9
43-6013	Medical Secretaries and Administrative Assistants	0.36	—	21.7	2.9
25-1123	English Language and Literature Teachers, Postsecondary	0.36	—	3.3	1.3
25-1032	Engineering Teachers, Postsecondary	0.36	—	10.8	-2.9
27-1014	Special Effects Artists and Animators	0.36	—	-40.9	-7.7
27-1013	Fine Artists, Including Painters, Sculptors and Illustrators	0.36	—	-17.2	1.9
13-2052	Personal Financial Advisors	0.35	—	-4.4	8.4
13-2011	Accountants and Auditors	0.35	—	3.3	0.4
27-3092	Court Reporters and Simultaneous Captioners	0.34	—	-11.3	-1.1
15-1221	Computer and Information Research Scientists	0.34	—	13.9	-9.0
15-1244	Network and Computer Systems Administrators	0.34	—	-2.3	-3.0
15-1242	Database Administrators	0.33	—	-9.1	-2.4
41-9031	Sales Engineers	0.32	—	-5.0	-3.2
41-2031	Retail Salespersons	0.32	—	4.4	-0.4
25-1066	Psychology Teachers, Postsecondary	0.32	—	3.9	-1.5
41-3021	Insurance Sales Agents	0.32	—	5.4	-1.3
19-4031	Chemical Technicians	0.31	—	-0.7	1.6
23-1023	Judges, Magistrate Judges and Magistrates	0.31	—	-9.4	-13.3
15-1299	Computer Occupations, All Other	0.31	—	5.5	3.9
43-3031	Bookkeeping, Accounting and Auditing Clerks	0.31	—	-6.1	2.2
25-1011	Business Teachers, Postsecondary	0.31	—	4.3	-1.9
29-9021	Health Information Technologists and Medical Registrars	0.31	—	6.0	4.8
23-1021	Administrative Law Judges, Adjudicators and Hearing Officers	0.30	—	29.9	17.5
25-1071	Health Specialties Teachers, Postsecondary	0.30	—	10.6	0.6

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
25-9031	Instructional Coordinators	0.30	—	6.1	-1.1
43-3011	Bill and Account Collectors	0.30	—	-18.6	5.2
25-2022	Middle School Teachers, Except Special and Career/Technical Education	0.30	—	1.5	-3.8
23-2011	Paralegals and Legal Assistants	0.29	—	6.4	-1.4
25-1042	Biological Science Teachers, Postsecondary	0.29	—	6.7	-3.5
25-2031	Secondary School Teachers, Except Special and Career/Technical Education	0.29	—	2.9	-1.2
15-1252	Software Developers	0.29	—	7.8	1.3
15-1231	Computer Network Support Specialists	0.29	—	-13.3	-2.5
41-9041	Telemarketers	0.29	—	-31.2	0.8
41-9022	Real Estate Sales Agents	0.28	—	-1.2	0.4
13-1151	Training and Development Specialists	0.28	—	18.9	-1.7
43-4021	Correspondence Clerks	0.28	—	26.0	2.0
15-1211	Computer Systems Analysts	0.28	—	-1.5	-3.0
19-2012	Physicists	0.27	—	13.3	3.0
41-4011	Sales Representatives, Wholesale and Manufacturing, Technical and Scientific Products	0.27	—	1.1	-3.0
13-2054	Financial Risk Specialists	0.26	—	0.9	-3.8
41-1011	First-Line Supervisors of Retail Sales Workers	0.26	—	1.5	-2.7
25-1081	Education Teachers, Postsecondary	0.26	—	1.4	-6.9
19-2031	Chemists	0.26	—	-0.8	-1.3
41-9021	Real Estate Brokers	0.26	—	-5.2	-6.1
15-1255	Web and Digital Interface Designers	0.25	—	14.4	2.0
43-4181	Reservation and Transportation Ticket Agents and Travel Clerks	0.25	—	7.0	-2.2
27-3043	Writers and Authors	0.25	—	-11.5	-12.7
27-3041	Editors	0.25	—	-5.9	-5.9
19-1029	Biological Scientists, All Other	0.25	—	8.0	-2.5
29-2051	Dietetic Technicians	0.24	—	52.1	1.3
43-3061	Procurement Clerks	0.24	—	-5.4	0.9
13-1111	Management Analysts	0.24	—	10.5	2.1
23-1022	Arbitrators, Mediators and Conciliators	0.24	—	1.0	-14.1
19-3011	Economists	0.24	—	-3.0	-4.9
25-1021	Computer Science Teachers, Postsecondary	0.24	—	7.0	-0.0
25-1124	Foreign Language and Literature Teachers, Postsecondary	0.24	—	8.5	-2.0
43-9022	Word Processors and Typists	0.24	—	-14.2	3.0
13-2071	Credit Counselors	0.23	—	-3.4	0.8
43-6011	Executive Secretaries and Executive Administrative Assistants	0.23	—	-0.5	1.0

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
41-1012	First-Line Supervisors of Non-Retail Sales Workers	0.23	—	-7.8	-5.9
19-4043	Geological Technicians, Except Hydrologic Technicians	0.23	—	5.9	-10.8
43-5032	Dispatchers, Except Police, Fire and Ambulance	0.23	—	2.2	2.4
27-4032	Film and Video Editors	0.22	—	-10.0	-3.9
13-2099	Financial Specialists, All Other	0.22	—	0.3	4.6
25-1126	Philosophy and Religion Teachers, Postsecondary	0.22	—	-3.6	-5.7
25-1052	Chemistry Teachers, Postsecondary	0.22	—	-1.3	0.8
25-1121	Art, Drama, and Music Teachers, Postsecondary	0.21	—	0.1	1.9
25-1122	Communications Teachers, Postsecondary	0.21	—	7.0	-0.6
15-2041	Statisticians	0.21	—	-3.2	-0.8
27-1011	Art Directors	0.21	—	-7.5	-4.0
27-3023	News Analysts, Reporters and Journalists	0.21	—	-6.7	14.5
41-2021	Counter and Rental Clerks	0.20	—	7.5	3.5
19-4013	Food Science Technicians	0.20	—	-1.0	-1.3
25-4022	Librarians and Media Collections Specialists	0.20	—	0.1	-0.5
43-4131	Loan Interviewers and Clerks	0.20	—	-28.7	1.7
29-1224	Radiologists	0.20	—	-10.1	1.9
15-1241	Computer Network Architects	0.20	—	1.8	-2.2
27-4021	Photographers	0.20	—	8.1	3.3
43-3021	Billing and Posting Clerks	0.19	—	-5.5	2.9
25-1072	Nursing Instructors and Teachers, Postsecondary	0.19	—	7.3	-3.6
39-6012	Concierges	0.19	—	17.6	-0.8
13-2072	Loan Officers	0.19	—	-15.9	-4.8
43-1011	First-Line Supervisors of Office and Administrative Support Workers	0.19	—	0.0	1.8
13-1199	Business Operations Specialists, All Other	0.18	—	4.3	4.1
19-2032	Materials Scientists	0.18	—	9.3	-6.2
43-9081	Proofreaders and Copy Markers	0.18	—	0.8	0.7
41-9091	Door-to-Door Sales Workers, News and Street Vendors and Related Workers	0.18	—	-46.9	2.4
43-4011	Brokerage Clerks	0.17	—	-6.1	6.5
43-4081	Hotel, Motel and Resort Desk Clerks	0.17	—	7.5	6.8
23-1012	Judicial Law Clerks	0.17	—	-14.9	-1.9
13-2041	Credit Analysts	0.17	—	-6.4	-0.9
23-1011	Lawyers	0.17	—	5.7	4.0
27-4031	Camera Operators, Television, Video and Film	0.17	—	6.5	6.4
19-3032	Industrial-Organizational Psychologists	0.16	—	-18.0	-13.4
29-1222	Physicians, Pathologists	0.16	—	-4.2	-2.0
13-1081	Logisticians	0.16	—	16.1	0.5
43-4071	File Clerks	0.16	—	-9.5	2.9

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
25-1194	Career/Technical Education Teachers, Postsecondary	0.16	—	7.8	-2.3
21-2021	Directors, Religious Activities and Education	0.15	—	-10.7	0.1
41-3011	Advertising Sales Agents	0.15	—	-8.5	-2.9
43-9041	Insurance Claims and Policy Processing Clerks	0.15	—	0.7	1.2
17-2061	Computer Hardware Engineers	0.15	—	1.4	3.7
19-4042	Environmental Science and Protection Technicians, Including Health	0.14	—	16.1	-2.0
11-1021	General and Operations Managers	0.14	—	6.2	0.9
21-1091	Health Education Specialists	0.14	—	15.9	0.1
19-3091	Anthropologists and Archeologists	0.14	—	9.8	-3.1
25-4011	Archivists	0.13	—	-2.5	-1.5
25-2057	Special Education Teachers, Middle School	0.13	—	14.9	-3.1
29-1031	Dietitians and Nutritionists	0.13	—	9.6	0.4
17-2031	Bioengineers and Biomedical Engineers	0.13	—	13.8	-0.8
43-4041	Credit Authorizers, Checkers, and Clerks	0.13	—	-26.6	3.4
13-2082	Tax Preparers	0.13	—	-10.7	-1.8
33-3051	Police and Sheriff's Patrol Officers	0.12	—	1.7	3.5
13-1041	Compliance Officers	0.12	—	10.6	2.8
51-9162	Computer Numerically Controlled Tool Programmers	0.12	—	0.4	0.8
21-1012	Educational, Guidance, and Career Counselors and Advisors	0.12	—	11.2	3.8
13-1011	Agents and Business Managers of Artists, Performers and Athletes	0.12	—	8.3	28.4
53-6061	Passenger Attendants	0.12	—	92.0	-1.1
25-1193	Recreation and Fitness Studies Teachers, Postsecondary	0.11	—	-5.4	-0.1
21-2011	Clergy	0.11	—	9.3	4.0
19-3092	Geographers	0.11	—	1.5	2.8
37-1012	First-Line Supervisors of Landscaping, Lawn Service and Groundskeeping Workers	0.11	—	1.0	-0.8
49-2011	Computer, Automated Teller and Office Machine Repairers	0.11	—	-10.4	-1.5
25-2021	Elementary School Teachers, Except Special Education	0.10	—	-0.1	-4.4
17-3025	Environmental Engineering Technologists and Technicians	0.10	—	-6.7	1.3
13-1121	Meeting, Convention and Event Planners	0.10	—	20.2	3.2
43-4031	Court, Municipal and License Clerks	0.10	—	6.4	3.1
51-5111	Prepress Technicians and Workers	0.10	—	-8.6	2.0
49-1011	First-Line Supervisors of Mechanics, Installers and Repairers	0.10	—	7.4	1.6

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
25-9044	Teaching Assistants, Postsecondary	0.10	—	14.7	5.7
17-2072	Electronics Engineers, Except Computer	0.10	—	-11.9	4.2
25-1125	History Teachers, Postsecondary	0.10	—	8.8	-1.5
25-2058	Special Education Teachers, Secondary School	0.10	—	6.7	-2.5
43-4121	Library Assistants, Clerical	0.10	—	3.1	3.9
19-1022	Microbiologists	0.10	—	0.3	-0.3
19-3051	Urban and Regional Planners	0.10	—	7.9	1.4
19-4099	Life, Physical, and Social Science Technicians, All Other	0.10	—	0.9	4.2
29-1171	Nurse Practitioners	0.09	—	19.0	-1.4
43-5061	Production, Planning and Expediting Clerks	0.09	—	-1.3	2.2
29-1131	Veterinarians	0.09	—	2.3	1.2
27-2012	Producers and Directors	0.09	—	-5.5	-3.8
21-1022	Healthcare Social Workers	0.09	—	1.9	6.9
53-2031	Flight Attendants	0.09	—	19.9	9.7
29-1051	Pharmacists	0.09	—	1.0	-1.2
17-3012	Electrical and Electronics Drafters	0.09	—	-4.3	5.8
41-2011	Cashiers	0.08	—	-4.5	3.1
29-1216	General Internal Medicine Physicians	0.08	—	-0.9	8.6
13-1031	Claims Adjusters, Examiners and Investigators	0.08	—	6.9	-0.0
17-2141	Mechanical Engineers	0.08	—	3.3	1.7
27-2032	Choreographers	0.08	—	-36.5	-1.6
17-1021	Cartographers and Photogrammetrists	0.08	—	-3.6	2.5
41-9011	Demonstrators and Product Promoters	0.08	—	49.2	5.9
17-1011	Architects, Except Landscape and Naval	0.08	—	3.4	-0.2
17-3022	Civil Engineering Technologists and Technicians	0.08	—	-0.4	3.7
19-1021	Biochemists and Biophysicists	0.08	—	6.2	-6.2
17-2011	Aerospace Engineers	0.08	—	11.1	3.5
19-2043	Hydrologists	0.07	—	-8.8	-5.1
43-4151	Order Clerks	0.07	—	-26.5	6.3
29-2052	Pharmacy Technicians	0.07	—	7.6	3.7
35-9031	Hosts and Hostesses, Restaurant, Lounge and Coffee Shop	0.07	—	6.7	5.1
39-6011	Baggage Porters and Bellhops	0.07	—	17.7	3.9
51-8092	Gas Plant Operators	0.07	—	11.3	1.5
29-1218	Obstetricians and Gynecologists	0.07	—	-7.2	-5.6
17-3027	Mechanical Engineering Technologists and Technicians	0.07	—	-5.5	4.6
13-2031	Budget Analysts	0.07	—	-2.6	-0.2
39-9041	Residential Advisors	0.07	—	-4.6	3.2
25-3021	Self-Enrichment Teachers	0.07	—	24.3	-1.3

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
31-2012	Occupational Therapy Aides	0.07	—	34.8	-9.5
17-2199	Engineers, All Other	0.07	—	0.2	1.9
43-3041	Gambling Cage Workers	0.07	—	15.0	7.8
13-1141	Compensation, Benefits and Job Analysis Specialists	0.06	—	9.4	1.7
25-3011	Adult Basic Education, Adult Secondary Education, and English as a Second Language Instructors	0.06	—	-0.6	-4.6
27-3011	Broadcast Announcers and Radio Disc Jockeys	0.06	—	-11.0	-52.1
13-2053	Insurance Underwriters	0.06	—	1.8	2.0
39-3091	Amusement and Recreation Attendants	0.06	—	14.5	3.0
19-1023	Zoologists and Wildlife Biologists	0.06	—	-2.8	-0.0
19-4021	Biological Technicians	0.06	—	3.4	0.9
43-4061	Eligibility Interviewers, Government Programs	0.06	—	4.3	0.5
29-1141	Registered Nurses	0.06	—	6.8	3.0
19-3033	Clinical and Counseling Psychologists	0.06	—	14.8	-3.1
17-2071	Electrical Engineers	0.06	—	3.6	-1.2
33-9099	Protective Service Workers, All Other	0.06	—	-11.4	3.8
27-1022	Fashion Designers	0.06	—	1.7	33.0
35-1012	First-Line Supervisors of Food Preparation and Serving Workers	0.06	—	1.5	2.0
19-2041	Environmental Scientists and Specialists, Including Health	0.05	—	9.9	-1.5
25-4031	Library Technicians	0.05	—	0.6	-1.2
15-2011	Actuaries	0.05	—	13.3	-1.4
27-1012	Craft Artists	0.05	—	-8.2	-14.1
29-9091	Athletic Trainers	0.05	—	-2.6	3.1
29-1161	Nurse Midwives	0.05	—	4.2	-2.5
29-2033	Nuclear Medicine Technologists	0.05	—	0.3	3.6
19-1013	Soil and Plant Scientists	0.05	—	3.7	1.2
51-2011	Aircraft Structure, Surfaces, Rigging and Systems Assemblers	0.05	—	2.3	3.1
47-2221	Structural Iron and Steel Workers	0.05	—	-3.1	-0.4
43-3051	Payroll and Timekeeping Clerks	0.05	—	-1.4	1.3
47-4011	Construction and Building Inspectors	0.05	—	6.4	1.5
53-2022	Airfield Operations Specialists	0.05	—	12.7	-2.4
31-9092	Medical Assistants	0.05	—	5.4	2.4
19-3034	School Psychologists	0.05	—	5.9	-0.4
13-1131	Fundraisers	0.05	—	11.9	2.2
43-5031	Public Safety Telecommunicators	0.05	—	5.7	3.4
37-2021	Pest Control Workers	0.05	—	5.4	1.1
29-2099	Health Technologists and Technicians, All Other	0.04	—	6.9	3.4

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
39-1014	First-Line Supervisors of Entertainment and Recreation Workers, Except Gambling Services	0.04	—	17.4	-1.5
47-2132	Insulation Workers, Mechanical	0.04	—	-0.1	0.2
27-1021	Commercial and Industrial Designers	0.04	—	-0.7	0.3
37-1011	First-Line Supervisors of Housekeeping and Janitorial Workers	0.04	—	5.4	0.5
19-2042	Geoscientists, Except Hydrologists and Geographers	0.04	—	-10.8	-0.8
13-2061	Financial Examiners	0.04	—	-0.9	1.0
51-9021	Crushing, Grinding, and Polishing Machine Setters, Operators, and Tenders	0.04	—	4.5	1.6
43-5021	Couriers and Messengers	0.04	—	-5.1	2.9
49-9061	Camera and Photographic Equipment Repairers	0.04	—	-5.2	6.2
39-1022	First-Line Supervisors of Personal Service Workers	0.04	—	2.5	0.2
51-8093	Petroleum Pump System Operators, Refinery Operators, and Gaugers	0.04	—	11.2	0.7
29-1129	Therapists, All Other	0.04	—	14.2	-4.3
25-1051	Atmospheric, Earth, Marine and Space Sciences Teachers, Postsecondary	0.04	—	3.0	-2.2
51-9198	Helpers–Production Workers	0.04	—	-12.2	4.5
51-2061	Timing Device Assemblers and Adjusters	0.04	—	-37.8	-15.0
29-2035	Magnetic Resonance Imaging Technologists	0.04	—	8.2	4.0
19-1042	Medical Scientists, Except Epidemiologists	0.04	—	41.4	-5.1
19-2021	Atmospheric and Space Scientists	0.04	—	-11.3	3.5
19-2099	Physical Scientists, All Other	0.04	—	13.9	-1.4
33-3021	Detectives and Criminal Investigators	0.04	—	3.2	0.4
27-2041	Music Directors and Composers	0.04	—	5.5	-17.8
17-2112	Industrial Engineers	0.04	—	9.0	2.0
17-2081	Environmental Engineers	0.04	—	-16.5	1.3
17-2121	Marine Engineers and Naval Architects	0.04	—	13.3	3.0
51-6052	Tailors, Dressmakers and Custom Sewers	0.03	—	-3.4	10.2
11-1011	Chief Executives	0.03	—	6.3	-0.6
49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers	0.03	—	-8.5	0.7
19-3099	Social Scientists and Related Workers, All Other	0.03	—	11.3	4.9
51-9061	Inspectors, Testers, Sorters, Samplers and Weighers	0.03	—	2.0	1.8
51-9032	Cutting and Slicing Machine Setters, Operators and Tenders	0.03	—	-12.1	3.0
51-6063	Textile Knitting and Weaving Machine Setters, Operators and Tenders	0.03	—	-14.0	3.0
33-1011	First-Line Supervisors of Correctional Officers	0.03	—	-4.5	9.2
29-1021	Dentists, General	0.03	—	-6.0	6.0

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
39-5012	Hairdressers, Hairstylists and Cosmetologists	0.03	—	-0.9	4.1
49-2098	Security and Fire Alarm Systems Installers	0.03	—	1.0	3.0
51-7032	Patternmakers, Wood	0.03	—	-45.5	18.0
29-1229	Physicians, All Other	0.03	—	3.3	-1.1
47-1011	First-Line Supervisors of Construction Trades and Extraction Workers	0.03	—	11.8	1.4
53-3031	Driver/Sales Workers	0.03	—	-14.7	3.9
47-2061	Construction Laborers	0.03	—	4.4	3.0
19-3093	Historians	0.03	—	0.6	0.3
13-2081	Tax Examiners and Collectors, and Revenue Agents	0.03	—	5.8	-2.3
25-2059	Special Education Teachers, All Other	0.03	—	-8.0	-7.0
51-8013	Power Plant Operators	0.03	—	-2.8	0.5
49-9041	Industrial Machinery Mechanics	0.02	—	9.3	2.6
43-9071	Office Machine Operators, Except Computer	0.02	—	-18.6	1.2
25-1061	Anthropology and Archeology Teachers, Postsecondary	0.02	—	6.7	-3.5
25-1053	Environmental Science Teachers, Postsecondary	0.02	—	14.3	2.2
43-3071	Tellers	0.02	—	-3.7	3.6
29-1299	Healthcare Diagnosing or Treating Practitioners, All Other	0.02	—	2.6	-3.3
19-4071	Forest and Conservation Technicians	0.02	—	6.7	17.3
31-9095	Pharmacy Aides	0.02	—	-4.9	4.6
23-2093	Title Examiners, Abstractors and Searchers	0.02	—	-10.3	-2.6
51-9161	Computer Numerically Controlled Tool Operators	0.02	—	-1.3	2.8
51-6061	Textile Bleaching and Dyeing Machine Operators and Tenders	0.02	—	-12.3	7.2
25-1043	Forestry and Conservation Science Teachers, Postsecondary	0.02	—	3.1	-1.5
45-2092	Farmworkers and Laborers, Crop, Nursery and Greenhouse	0.02	—	-7.9	2.8
17-3023	Electrical and Electronic Engineering Technologists and Technicians	0.02	—	-6.4	3.4
27-4012	Broadcast Technicians	0.02	—	-36.2	-29.5
49-9021	Heating, Air Conditioning and Refrigeration Mechanics and Installers	0.02	—	5.9	1.6
25-1082	Library Science Teachers, Postsecondary	0.02	—	-5.3	-3.9
31-9096	Veterinary Assistants and Laboratory Animal Caretakers	0.02	—	2.1	5.3
29-1123	Physical Therapists	0.02	—	8.2	-2.6
27-4011	Audio and Video Technicians	0.02	—	24.9	-0.9
43-5011	Cargo and Freight Agents	0.02	—	4.6	3.8

SOC Code	Occupation	Anthropic Score	High Exposure	△ Emp (%)	△ Real Wage (%)
47-2181	Roofers	0.02	—	3.6	2.5
51-6062	Textile Cutting Machine Setters, Operators and Tenders	0.02	—	-16.3	2.6
29-9092	Genetic Counselors	0.01	—	9.0	2.9
39-9011	Childcare Workers	0.01	—	13.2	4.4
35-2014	Cooks, Restaurant	0.01	—	9.9	3.6
47-2152	Plumbers, Pipefitters and Steamfitters	0.01	—	6.5	-0.1
51-9151	Photographic Process Workers and Processing Machine Operators	0.01	—	3.2	0.3
17-2051	Civil Engineers	0.01	—	15.6	2.4
29-1122	Occupational Therapists	0.01	—	12.8	-1.4
21-1021	Child, Family and School Social Workers	0.01	—	11.1	3.4
25-2051	Special Education Teachers, Preschool	0.01	—	22.8	-2.8
19-4012	Agricultural Technicians	0.01	—	9.1	1.4
17-1022	Surveyors	0.00	—	11.1	0.6
11-1031	Legislators	0.00	—	-38.2	-11.7