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AI and Wage Inequality in the United States, 2010-2024: Why Theory and Data Diverge

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ABSTRACT

This paper investigates the impact of artificial intelligence on wage inequality and labor market equilibria within the United States between the years 2010 and 2024. Task-based economic models predict that artificial intelligence should displace routine middle-skill jobs while enhancing the efficiency of high-skill work, leading to an increase in wage polarization.

However, analysis of data from the Bureau of Labor Statistics (BLS) reveals an unexpected pattern. The 90/10 wage ratio decreased from 4.70 to 4.19 during the period of time that this study covers, even as the AI Adoption Index increased from 0.05 to 0.65. Decomposition by occupational skill group reveals distinct wage growth patterns. High-skill wages grew by approximately 45 percent, middle-skill wages by 48 percent. Low-skill wages rose most sharply at 61 percent, with the lowest-paid workers seeing the greatest gains.

This finding contradicts the hollowing out hypothesis. It particularly suggests that other structural forces such as minimum wage increases, post-COVID labor market tightness, and policy interventions, exceeded automation's polarizing effects during this period.

A lagged robustness check confirms that the negative association between artificial intelligence adoption and wage inequality still holds when AI adoption precedes wage gap movements by one year. The divergence between theoretical predictions and empirical results highlights a key point. Institutional factors mediate technology's labor market effects. This suggests task-based automation theories need refinement. They must account for countervailing policy and market forces.

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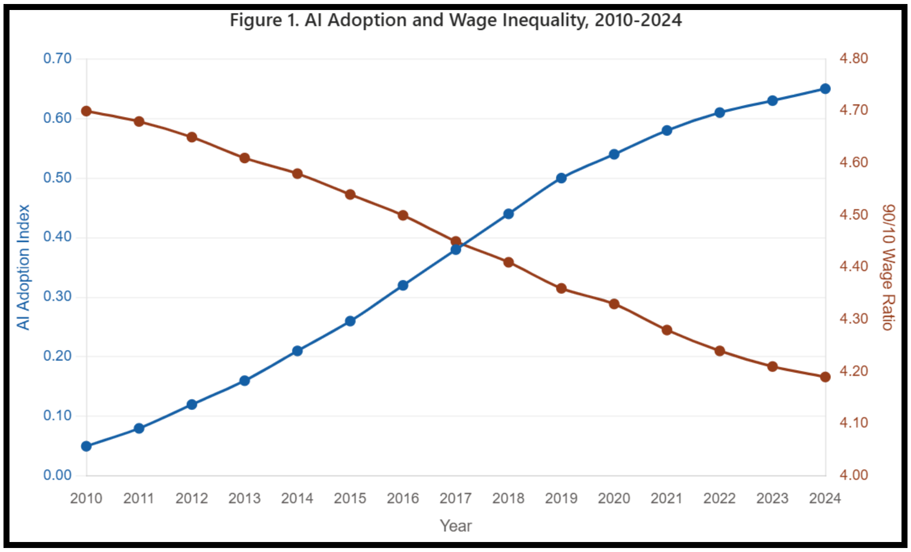

Figure 1. *AI Adoption and Wage Inequality, 2010-2024. Author's calculations based on BLS Occupational Employment and Wage Statistics and OECD/Stanford AI adoption indices.*

1. INTRODUCTION

Artificial intelligence has transformed from a niche research area into a central driver of economic activity, reshaping numerous fields such as logistics, finance, healthcare, and beyond. This diffusion raises an extremely important labor economics question. How do AI-driven productivity shocks affect labor market equilibrium and the distribution of wages? This study examines whether rising artificial intelligence use is associated with earnings polarization, specifically a relative decline in middle-skill, routine-task employment and a corresponding rise in demand for high-skill cognitive work.

The analysis is grounded in task based economic theory, which highlights the difference between technologies that substitute for tasks and those that complement them. Under this framework, AI acts as both a substitution mechanism that displaces routine cognitive and data-processing tasks and a creation mechanism that generates new roles in AI design, deployment, and governance. The main hypothesis is that during the time period of study between 2010 and 2024, substitution effects dominated creation effects in middle-skill occupations, producing polarization in the wage distribution.

This question carries a lot of urgency given the period under study, which includes the rise of deep learning, the large scale arrival of generative AI tools such as ChatGPT in late 2022, and U.S. private investments in artificial intelligence reaching tens of billions of dollars annually. If these technologies disproportionately reward certain skills while displacing others, they can lead to a structural shift towards an increase in inequality that goes beyond earlier automation waves.

To further explore and better understand these dynamics, the paper constructs a 15-year panel combining BLS Occupational Employment and Wage Statistics (2010 to 2024) with a composite AI Adoption Index developed from OECD and Stanford sources. The resulting analysis reveals a surprising pattern. While the AI index rises dramatically from 0.05 to 0.65, the 90/10 wage gap actually narrows from 4.70 to 4.19. Skill-group decomposition shows the large scale variance in growth levels across groups. Low skill wage growth of 61 percent, middle skill growth of 48 percent, and high skill growth of 45 percent. These results show the inverse of the predicted hollowing-out pattern. This paper explores why observed trends contradicted theoretical expectations and what this reveals about the complex interplay between technology and labor market institutions.

2. RELATED LITERATURE

There have been many examples throughout history where productivity shocks have disrupted labor market equilibrium and reshaped wage structures. The Industrial Revolution mechanized the production of agriculture and textiles, and computerization in the 1980s and 1990s automated clerical routines while leading to an increase in the demand for programmers and analysts (Autor & Katz, 2010). When a large technology shock arrives, it leads to a disturbance in the supply-demand equilibrium, and wages adjust as tasks are reallocated across occupations (Acemoglu, 2024). Wage polarization describes the typical outcome: pay at the top and bottom of the distribution rises relative to the middle, with middle-skill workers in routine cognitive and manual jobs losing out most (Autor & Katz, 2010).

AI differs from prior technologies in scope and task targeting. Acemoglu and Restrepo's task-based framework highlights two opposing forces. Displacement occurs as machines take over existing tasks. Reinstatement happens when new tasks emerge that restore labor demand (Acemoglu & Restrepo, 2019). Their emprical work on industrial robots finds that each additional robot per thousand workers reduces employment-to-population ratios and depresses wages, with displacement dominating in the medium run (Acemoglu & Restrepo, 2020). Their analysis of AI specifically warns that modern systems can perform a greater range of cognitive tasks, raising the risk of excessive amounts of automation when institutional incentives demonstrate a preference for capital substitution over task creation (Acemoglu & Restrepo, 2019). At the macroeconomic level, Acemoglu (2024) argues that aggregate productivity gains from AI may be moderate relative to expectations, but distributional effects can be of substantial scale if AI raises the capital share of income and suppresses wages for exposed groups.

Webb (2020) offers complementary evidence using text based patent matching to occupational task descriptions. Robots with primary industrial focus threaten routine physical work and software automation threatens middle skill clerical roles while AI patents mostly target high skill cognitive abilities such as reading comprehension, complex information processing, and aspects of social interaction. This suggests that artificial intelligence may penetrate white-collar professional work more deeply than prior technologies. Tolan et al. (2021) reinforce this finding by linking a connection between occupational tasks to AI benchmark performance and documenting strong AI progress in pattern recognition, visual processing, and text processing. Critically, they find that complete levels of occupational automation remain highly unlikely and that AI instead reshapes the composition of tasks within jobs. Septiandri, Constantinides, and Quercia (2024) extend this work by using methods involving deep learning to distinguish consolidating AI, which streamlines existing routines, from disruptive AI that alters non routine cognitive tasks, documenting heterogeneous effects across sectors and occupations.

Jia (2024) applies a task-based framework with multiple nuances, showing that artificial intelligence contributes to the spread of polarization. It substitutes for routine and some higher skill cognitive tasks while complementing creative, problem-solving, and interpersonal work. She also argues that AI weakens worker bargaining power in non-automated jobs. It does this by improving employers' outside options. This could lead to potentially decoupling wage growth from productivity gains. Ganuthula and Balaraman (2025) compare India and the U.S. from 2018-2023. The U.S. shows clear hollowing out, with growth present in high-skill jobs and a decline in middle-skill occupations. India exhibits less polarization, tied to its low-skill labor structure. Sun (2025) and Castello (2025) bring together these ideas from a policy aligned viewpoint. They argue that AI has a nature of duality. It improves productivity for some people while displacing others. This situation calls for proactive changes in education systems and active labor market policies to stop increasing inequality.

This literature supports the main idea discussed. AI-driven changes will likely displace routine middle-skill jobs more than they will create similar new opportunities for that group. At the same time, these changes will support higher-skill roles while having a smaller impact on many low-skill non-routine jobs (Acemoglu & Restrepo, 2019; Jia, 2024; Tolan et al., 2021). Most existing work focuses on local robot shocks, measures of exposure at a specific point in time, or short windows that come before the generative AI era.

3. DATA AND METHODOLOGY

3.1 Data Processing

Hourly wage data are drawn from the BLS Occupational Employment and Wage Statistics (OEWS) program, which reports annual wage percentiles by occupation. The 90th-percentile wage proxies high-skill pay and the 10th-percentile wage proxies low-skill pay; occupations are categorized into high-, middle-, and low-skill groups using Standard Occupational Classification (SOC) codes, enabling skill-level wage tracking across the full 2010 to 2024 panel.

I classify occupations into three skill categories based on factors such as educational requirements, complexity of tasks, and wage levels. High skill occupations are jobs that require higher education degrees and training. These occupations include managers, financial analysts, software developers, lawyers, doctors, and those that work in education. Middle skill occupations are made up of two primary categories. Technical trades such as construction, equipment maintenance, and manufacturing, and routine cognitive positions such as administrative support, sales, and protective services. Low skill jobs are generally service jobs that require little or no formal education. Examples include restaurant workers, health care assistants, janitors, and personal care attendants. Complete Standard Occupational

Classification (SOC) codes for each category appear in Appendix A. For each skill group, employment-weighted average hourly wages are calculated across all included SOC major groups.

BLS OEWS wages are published in current (nominal) dollars. To account for inflation, I apply the BLS Consumer Price Index for All Urban Consumers (CPI-U) annual averages, deflating all wage series to constant 2010 dollars (CPI-U 2010 = 218.056; 2024 = 314.175; deflator = 0.694). Both nominal and real results are reported throughout. Because the 90/10 ratio divides two wages by the same deflator, the ratio itself is scale-invariant and identical in nominal and real terms.

The composite AI Adoption Index combines data from the OECD AI Policy Tracker and Stanford AI Index Report, aggregating four component series: (1) AI-related patent filings from the OECD, (2) private AI investment in billions USD from the Stanford HAI AI Index Report, (3) enterprise AI adoption rates from OECD employer surveys, and (4) AI policy readiness scores from the OECD AI Policy Tracker. Each component series was normalized to a 0 to 1 scale using min-max normalization over the 2010 to 2024 period. The four normalized components were then averaged with equal weights (0.25 each) to produce the composite index scaled from 0 to 1. Equal weighting was chosen in the absence of a theoretical basis for preferring one dimension of AI diffusion over another at national aggregate level. One missing observation (2011) was imputed via linear interpolation between adjacent years.

3.2 Data Processing

Annual wage and AI series are merged by calendar year. The primary outcome variable is the 90/10 wage gap, defined as the ratio of 90th- to 10th-percentile wages, which serves as the summary measure of wage polarization.

3.3 Analytical Approach

The empirical strategy proceeds in three steps. First, descriptive time-series plots document the joint evolution of the AI Adoption Index and the 90/10 wage gap alongside skill-group wage changes. Second, Pearson correlation coefficients quantify the strength of association between AI adoption and wage polarization. Third, a simple linear regression relates the wage gap to AI adoption:

$$WageGapt = \alpha + \beta \; AIIndext + \varepsilon t$$

where t indexes years. An additional specification introduces a one-year lag on the AI Adoption Index to examine whether AI intensity changes precede wage gap movements.

This regression estimates the bivariate relationship between AI adoption and wage inequality. The coefficient β measures the mean difference in the 90/10 wage ratio for a one-unit increase in the AI index. The estimate does not imply a causal relationship, given the national aggregate structure of the data and lack of controls for confounding factors such as trade policy, shifts in educational attainment, or regional labor market conditions. Instead, it measures the descriptive association between two national time series over the period of study.

The lagged specification addresses temporal ordering by testing whether prior-year AI adoption levels predict current wage gaps:

$$WageGapt = \alpha + \beta\ AIIndext\text{-}1 + \varepsilon t$$

A negative coefficient in this specification would indicate that increases in AI adoption precede narrowing wage gaps, consistent with the observed pattern but still subject to the same identification limitations. Additionally, a pre/post 2022 comparison uses the generative AI inflection point (ChatGPT launch, November 2022) as a structural break, comparing mean wage ratios before and after to provide a more direct robustness check on the compression finding. Both specifications use ordinary least squares (OLS) estimation with robust standard errors. To contextualize these national trends, skill-group decomposition examines employment-weighted wage growth separately for high-, middle-, and low-skill occupations. This allows for detection of differential impacts across the wage distribution that may be obscured in aggregate percentile measures.

3.4 Limitations

The design is explicitly descriptive rather than causal. With fifteen annual national observations and no controls for trade, education, or labor market institutions, the estimates cannot isolate AI's independent effect from other structural forces, and national aggregates obscure sectoral and regional heterogeneity. Crucially, because both the AI Adoption Index and the 90/10 wage ratio trend monotonically over the study period, it is not possible to fully separate an AI-specific effect from a shared time trend. This is a binding constraint of the data structure and is acknowledged throughout. The study period (2010 to 2024) may be too short to capture AI's full labor market effects, as generative AI tools like ChatGPT only emerged at scale in late 2022. Displacement effects may operate on longer time scales than observable in this window. The equal-weighting assumption in the AI Adoption Index is a further limitation; alternative weightings could shift index values, though the directional trend would be preserved. The AI Adoption Index was constructed from OECD and Stanford HAI primary sources; minor variation in index values may arise from data revisions in those underlying sources over time. These constraints are acknowledged throughout and the approach nonetheless documents how AI adoption and the U.S. wage distribution co-evolved across an important phase of AI deployment.

4. RESULTS

The empirical analysis reveals an unexpected finding. Rising AI adoption coincided with decreasing wage inequality in the United States between 2010 and 2024, contradicting task-based theoretical predictions.

4.1 Graphical Evidence

Figure 1 documents the joint evolution of the AI Adoption Index and the 90/10 wage gap from 2010 to 2024. As the AI index rises from approximately 0.05 in the early 2010s to approximately 0.65 by the mid-2020s, the wage gap decreases from 4.70 to 4.19, indicating that the wage distribution actually compressed rather than polarized during this period of rapid AI adoption. This pattern contradicts the theoretical prediction that AI-driven substitution would widen wage inequality.

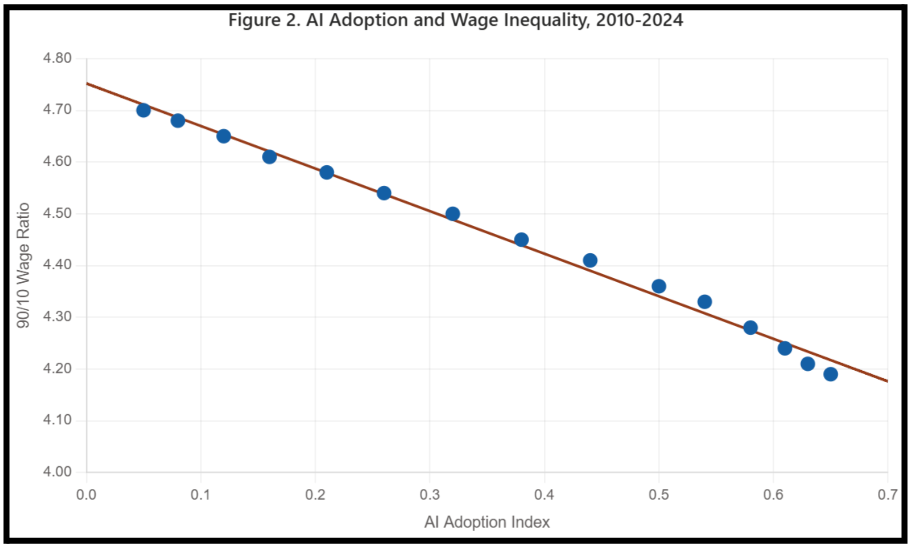

Figure 2. *AI Adoption and Wage Inequality, 2010-2024. Author's calculations based on U.S. Bureau of Labor Statistics, Occupational Employment and Wage Statistics (OEWS), and composite AI adoption indices constructed from OECD AI Policy Tracker and Stanford AI Index.*

4.2 Correlation and Regression Results

Figure 2 plots each annual observation against the fitted least-squares regression line. The bivariate regression yields $R^2 = 0.95$ with a negative slope coefficient. An R^2 this high between two time series is not that unusual. It does not establish meaningful causality. The results serve as descriptive correlation only. The negative slope shows higher AI adoption levels tie to narrower wage gaps. This runs opposite to task-based displacement theory predictions. For robustness, a lagged specification uses the prior year's AI index to predict the current wage gap. That yields $r = -0.94$. The negative association holds even when AI adoption precedes wage gap movements by one year. This does not solve identification challenges. Still, it confirms the relationship direction. A pre/post 2022 comparison provides additional context. Before 2022 (2010 to 2021), the mean 90/10 wage ratio was 4.45. After 2022 (2022 to 2024), the mean was 4.21, a decline of 0.24 ratio points, consistent with continued compression into the generative AI period. The post-2022 window contains only three observations, limiting strong inference, but the directional pattern holds.

4.3 Skill Group Decomposition

Detailed analysis of wage growth by skill category reveals the mechanism behind the unexpected compression:

2010 Wages (employment-weighted averages):
- *High-skill: $34.32/hour*
- *Middle-skill: $17.53/hour*
- *Low-skill: $11.30/hour*

2024 Wages (employment-weighted averages):
- *High-skill: $49.65/hour*
- *Middle-skill: $26.02/hour*
- *Low-skill: $18.24/hour*

Percentage Growth (2010-2024):
- *High-skill: 45%*
- *Middle-skill: 48%*
- *Low-skill: 61%*

In real (CPI-U-adjusted, 2010 dollars) terms, high-skill wages grew by 0.4 percent, middle-skill wages by 3.0 percent, and low-skill wages by 12.1 percent. The rank ordering is preserved: low-skill workers saw the greatest gains in both nominal and real terms. Most nominal wage growth was offset by inflation, as CPI rose 44 percent over the period, but the compression pattern persists. The 10th percentile grew 17.6 percent in real terms versus 5.0 percent at the 90th percentile, confirming that wage compression is not an artifact of inflation.

Low-wage workers experienced the highest wage growth, followed by middle-skill workers, with high-skill workers seeing the slowest growth, demonstrating the inverse trend of the predicted hollowing-out pattern. Similarly, examining the overall wage distribution percentiles:

10th percentile: $8.51/hour (2010) → $14.42/hour (2024) = 69% growth
90th percentile: $39.97/hour (2010) → $60.44/hour (2024) = 51% growth

The 90/10 ratio declined from 4.70 to 4.19, representing an 11% reduction in wage inequality.
While these patterns are clear in the descriptive data, a more rigorous causal analysis would require controlling for exogenous variables that also experienced a shift during this period. These would include minimum wage policy changes, macroeconomic conditions, sector composition shifts, and regional labor market dynamics. The observed compression could reflect the combined influence of multiple structural

forces rather than AI's isolated effect. Future research incorporating state-level variation in AI exposure and policy environments could help disentangle these mechanisms.

5. DISCUSSION

The results present an interesting puzzle. Rapid AI adoption from 2010 to 2024 took place alongside a decrease in wage inequality in the United States, instead of an increase. The 90/10 wage gap narrowed, and low-skill workers saw the largest wage growth. This goes against predictions based on task-based theories. This section examines possible reasons for this divergence.

5.1 Institutional and Policy Factors

Several institutional forces likely dominated any polarizing effects of AI during this period:

Minimum Wage Policy: Aggressive minimum wage increases at state and local levels directly boosted the 10th percentile. While the federal minimum remained at $7.25/hour, effective minimum wages rose to $15-18/hour in many jurisdictions (California, New York, Seattle, etc.), compressing the bottom of the wage distribution. State-level analysis comparing wage trends in high-minimum-wage versus low-minimum-wage states could provide a direct test of this mechanism.

Post-COVID Labor Market Dynamics: The pandemic fundamentally altered bargaining power in low-wage sectors. Worker shortages in retail, food service, hospitality, and healthcare support gave employees unprecedented leverage. The "Great Resignation" forced employers to raise wages substantially to attract and retain staff. Essential worker policies highlighted the value of previously undervalued roles.

Geographic Variation in Labor Markets: Tight labor markets in growing metropolitan areas, combined with remote work enabling geographic arbitrage, may have raised reservation wages for low-skill workers more than for high-skill workers who already had geographic flexibility.

5.2 Comparison to Historical Technology Shocks

The Industrial Revolution, the computerization wave of the 1980s and 1990s, and industrial robotics in the 1990s and 2000s all reshaped labor demand and disturbed existing equilibria. What distinguishes modern AI is its reach into cognitive and white-collar work, domains historically considered safe from automation (Webb, 2020; Tolan et al., 2021). However, the evidence here suggests that AI's labor market effects may operate on longer time scales than captured in this 15-year window, or may be concentrated in specific occupations that are obscured by broad percentile measures.

5.3 Task-Based Theory and Its Limitations

The results challenge but do not invalidate task-based automation theory. Several interpretations are possible:

Timing Lags: AI's displacement effects may not yet be fully visible in aggregate wage data. The period 2010-2024 may represent an "investment phase" where AI adoption is rising but labor market impacts lag behind. Displacement could intensify in coming years as systems mature and diffuse more broadly.

Measurement Issues: National wage percentiles may not capture the granular task-level changes that task-based theory predicts. AI may be reshaping specific occupations in ways that don't yet show up in broad skill categories. Firm- or occupation-level analysis might reveal polarization masked by aggregation.

Heterogeneous Effects: AI may be polarizing within sectors while aggregate inequality falls due to between-sector shifts. For example, if AI-intensive industries are small relative to service sectors experiencing minimum wage-driven compression, aggregate trends could diverge from within-industry patterns.

Task Creation vs. Substitution: The reinstatement effect (creation of new AI-complementary tasks) may be stronger than anticipated. This appears particularly true in high-skilled occupations adapting to use AI tools rather than being displaced by them.

5.4 Implications for Labor Market Equilibrium

Despite the unexpected direction of wage changes, the relationship between AI and labor market equilibrium remains critical. The findings suggest that institutional factors like minimum wage policy, labor market tightness, and worker bargaining power can substantially mediate or even reverse technology's distributional effects. This implies that labor market equilibrium under automation is not technologically determined. It depends heavily on policy choices and market conditions instead.

5.5 Policy Recommendations

The evidence suggests policy played a crucial role in shaping how AI-driven shocks translated into wage outcomes during this period. Rather than viewing automation's effects as predetermined, the 2010-2024 experience demonstrates that institutional responses matter profoundly. Minimum wage policy appears to have effectively counteracted any automation-driven wage compression at the bottom of the distribution—the aggressive state and local wage floors enacted during this period coincided with the strongest wage gains among the lowest-paid workers, preventing AI from depressing low-skill wages as task-based theory might predict. This points to wage policy as a powerful tool for shaping distributional outcomes even amid rapid technological change.

Labor market institutions beyond wage floors also shaped the observed patterns. The post-pandemic labor shortage gave workers unprecedented bargaining power, forcing employers to raise wages substantially to attract and retain staff in tight markets. This suggests that policies maintaining full employment—through macroeconomic management, support for worker organizing, and active labor market programs—may prove as important as education and training initiatives in determining how automation's benefits and costs are distributed across the workforce.

Yet timing introduces critical uncertainty. The compression documented here may reflect a specific and potentially temporary confluence of factors: an acute post-pandemic labor shortage, unusually aggressive state minimum wage activism, and a period when AI adoption was rising but full displacement effects had not yet materialized. Whether this pattern persists or reverses as AI systems mature and diffuse more broadly remains an open question. Proactive policies to create AI-complementary tasks, strengthen education systems, and support worker transitions will prove essential if policymakers hope to prevent future polarization as the technology continues to evolve.

CONCLUSION

This study examined whether rising AI adoption between 2010 and 2024 is associated with changes in the U.S. wage structure, focusing on wage polarization and labor market equilibrium. Linking national BLS Occupational Employment and Wage Statistics to a composite AI Adoption Index, the analysis documents an unexpected negative relationship between AI intensity and the 90/10 wage gap. Rather than the predicted hollowing-out pattern, low-skill wages grew 61%, middle-skill wages grew 48%, and high-skill wages grew 45%, with the wage distribution compressing rather than polarizing.

These findings contradict task-based theoretical predictions and suggest that other structural forces—minimum wage increases, post-COVID labor market tightness, and institutional factors—outweighed automation's polarizing effects during this period. This does not invalidate task-based automation theory; rather, it demonstrates that technology's labor market effects are mediated by policy choices and market conditions.

Compared with earlier automation waves, modern AI reaches more deeply into white-collar cognitive work while simultaneously reshaping production, services, and information-processing tasks across the economy. The divergence between theoretical predictions and empirical observations highlights several possibilities: AI's displacement effects may operate on longer time scales not yet visible in the data; measurement at the national aggregate level may obscure occupation-specific polarization; or institutional interventions successfully counteracted polarizing forces during this period.

The observed wage compression occurred during a period of aggressive state and local minimum wage increases and unprecedented post-pandemic labor market tightness. Whether this pattern persists or reverses as AI systems mature depends on sustained policy attention to task creation, education and reskilling, worker bargaining power, and effective social protection. The findings suggest that labor market outcomes under automation are not technologically predetermined but shaped substantially by institutional responses.

Future work using richer identification strategies, state-level variation in AI exposure and policy environments, and more granular occupational measures will be essential to understanding whether the patterns documented here represent a stable equilibrium or a temporary deviation.

APPENDIX A: OCCUPATIONAL CLASSIFICATION

High-skill occupations: Management (SOC 11-0000), Business and Financial Operations (13-0000), Computer and Mathematical (15-0000), Architecture and Engineering (17-0000), Life, Physical, and Social Science (19-0000), Community and Social Service (21-0000), Legal (23-0000), Education, Training, and Library (25-0000), and Healthcare Practitioners and Technical (29-0000).

Middle-skill occupations: Arts, Design, Entertainment, Sports, and Media (27-0000), Protective Service (33-0000), Sales and Related (41-0000), Office and Administrative Support (43-0000), Construction and Extraction (47-0000), Installation, Maintenance, and Repair (49-0000), Production (51-0000), and Transportation and Material Moving (53-0000).

Low-skill occupations: Healthcare Support (31-0000), Food Preparation and Serving Related (35-0000), Building and Grounds Cleaning and Maintenance (37-0000), Personal Care and Service (39-0000), and Farming, Fishing, and Forestry (45-0000).

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