

Machines, Markets, and the Disappearing Middle:

AI and the Divided Job Market

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Wage Inequality Across OECD Countries, 2000–2024

Abstract

Looking into sixteen rich countries between 2000 and 2024 reveals a pattern: jobs once held by people without college degrees have shrunk sharply. In the U.S., such roles dropped fourteen full percentage points. Meanwhile, those at the top pulled ahead — pay growth there outpaced typical workers by more than fourfold. Behind these changes sits technology; machines doing tasks once handled by humans play a part. Figuring out exactly how much belongs to AI is not straightforward. Still, clues point toward automated systems nudging certain workers aside while lifting returns for others.

Drawing from OECD household records, robot deployment counts, Oxford's technology preparedness rankings, and U.S. job profiles, four statistical methods were applied — ordinary least squares, dual fixed factors, instrument-based analysis, and generalized moment estimation. Every model shows similar results: when a country scores higher on AI readiness by one standard deviation, its pre-tax income gap grows between 0.28 and 0.34 Gini units, even adjusting for import levels, labor unions, and public cash aid.

When nations have solid job market institutions, rising inequality slows even as AI spreads. Nordic states fall far below the predicted trend line. The U.S. and U.K. sit well above it. From these data patterns, four clear policy steps emerge for governments to consider.

Keywords: *AI automation, wage inequality, labor market polarization, OECD, institutional economics, Gini coefficient, skill-biased technological change*

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1. Introduction

Here is a puzzle economists still wrestle with. If a company swaps a person for automation, where does the extra output go? History offers hope — past shifts did clear old work but brought new kinds. Electric power, factory lines, computers — they erased roles while sparking fresh ones. Yet voices since around 2015 argue something has shifted. Machines driven by code may not follow earlier rules.

That argument is not one we aim to close here. Rather than pin down every detail, our focus turns to real-world patterns drawn from multiple nations over two decades. Starting from 2000 through 2024, how has actual AI use shaped pay gaps and affected jobs requiring moderate skills? In places where disruption showed up less sharply, what paths did they follow? Behind those outcomes lies variation — some governments acted early, others leaned on training, a few reshaped labor rules quietly.

The answer is yes for the first part, while institutions shape much of the second. This mix matters in practice. Were growing gaps simply baked into technology — like code inside language tools or robot motion — then options post-outcome narrow to sharing gains after the fact. Yet when identical advances yield varied results based on workplace norms, schooling paths, and union presence, those structures actively reshape effects. What shows up here backs that view.

One contribution stands out right away — a new composite measure of how deeply countries engage with AI, blending robot numbers, technology investment, and readiness scores into one indicator. Beyond that, this study shows how government systems shape outcomes, an angle often noted but rarely quantified in past work. Finally, findings push up to 2024, capturing shifts sparked by fast-moving generative tools that earlier data simply did not reach.

2. Literature Review

2.1 The Skill-Biased Technological Change Foundation

This study begins with the notion known as Skill-Biased Technological Change, first clearly laid out by Katz and Murphy in 1992. Not every worker feels technological advances the same way — higher-skilled people often gain more, while lower-skilled roles can be replaced. Between 1963 and 1987, wages for college graduates climbed sharply in the U.S.; behind this surge stood shifting demand fueled by new technologies favoring educated labor, overpowering any downward pressure from rising numbers of degree holders. Later, Acemoglu explored why innovation tends to lean toward boosting skilled workers instead of spreading benefits evenly — his answer came in the form of a framework where economic incentives steer progress along certain lines.

2.2 Routine Work Shifts From People to Machines

What started as a simple idea grew sharper when Autor, Levy, and Murnane split tasks into two kinds — one kind being things like data entry or running machines, so structured they can be turned into code. These repeatable jobs often vanish under automation's reach. Meanwhile,

activities that demand either deep thinking or basic hands-on effort tend to stick around, simply because they resist clear rules. This split ended up forecasting job trends with surprising accuracy.

This framework suggests jobs form a U-shape: rising at high and low skill levels, shrinking in between. Goos, Manning, and Salomons traced that trend through 16 European nations, backing the job polarization thesis well before today's surge in artificial intelligence.

2.3 The AI-Specific Literature, 2015–2024

Frey and Osborne pushed the idea of job polarization into today's technology landscape by suggesting nearly half of American jobs might face replacement through machines. Critics questioned this figure — Arntz, Gregory, and Zierahn pointed out flaws tied to overlooking differences in daily tasks across roles. Still, later studies have mostly backed the general trend.

Finding clear cause and effect takes a sharp turn in work by Acemoglu and Restrepo. Their angle: tracking how robots spread across industries and using that rollout to measure automation's real impact. Their 2022 work in *Econometrica* shows how AI shifts tasks without replacing them at the same pace — something past technologies usually balanced. One thing past research often misses is cross-country variation. This study steps in right there — untangling those mixed effects, country by country.

3. Methodology

3.1 Theoretical Framework

The core model positions workers across three skill tiers — high, mid, and low — each reacting differently when technology shifts what workers can produce. Wages at each level depend on the worker's position within this structure, captured in the following expression:

$$w(k) = \theta(k) \cdot f(A, L(k)) - \lambda(k) \cdot \Delta(AI)$$

Here, $\theta(k)$ stands for how technology boosts output. The term $f(A, L(k))$ shows how labor and capital combine to make goods. The parameter $\lambda(k)$ — bounded between zero and one — marks how routine a job is. Meanwhile, $\Delta(AI)$ reflects broad changes brought by artificial intelligence across sectors. When AI grows stronger, pay for mid-level skills tends to shrink, because machines perform similar work faster. Those with advanced training see their value edge upward when AI enters the scene, as smart tools fit naturally into complex analytical roles.

The size of $\lambda(k)$ is the key quantity. Where routines dominate work life, each forward step in AI use squeezes pay more. Think office roles, support jobs, behind-the-scenes technical positions — steady mid-income gigs where duties repeat in predictable ways. Adding a measure of institutional strength — union membership rates, wage floors, job training budgets, and rules on firing — changes outcomes. When worker protections are tighter, swapping people for artificial intelligence gets harder. Such setups may not stop new tools from arriving, yet they delay who feels the squeeze and how benefits spread.

The model therefore expects substantial differences between nations. Even if two places start using AI at the same pace, their levels of inequality might drift apart depending on labor rules. The U.S. and U.K., where markets move freely, stack up very differently against Germany, Denmark, or Sweden, where coordination shapes work life.

3.2 Data Sources

Starting in 2000 and running through 2022, the study tracks 16 OECD nations, amounting to 480 individual country-year observations. The dependent variable is the Gini coefficient for market income, drawn from the OECD Income Distribution Database. Using market income keeps the focus on what jobs and pay actually look like, making automation's real impact on wages clearer.

The AI Adoption Index is constructed as a composite of three components: robot density per thousand employees (International Federation of Robotics), the ICT capital share of national output (OECD Productivity Statistics), and the Oxford AI Readiness Index. Employment data by skill level comes from BLS, Eurostat, and ILO sources. Institutional controls include union membership rates, active labor market policy spending, minimum wage levels, and employment protection legislation.

Table 1. Data Sources and Coverage

Variable	Source	Period	Countries
Gini Coefficient	OECD Income Distribution Database	2000–2022	38
AI Readiness Index	Oxford Insights	2017–2022	194
Robot Density	IFR World Robotics Report	2000–2022	50
ICT Capital Share	OECD Productivity Statistics	2000–2022	38
Employment by Skill Tier	BLS / Eurostat / ILO	2000–2022	60+
Union Density	OECD ICTWSS	2000–2022	50
ALMP Spending	OECD Employment Outlook	2000–2022	38
Trade Openness	World Bank WDI	2000–2022	200+

Note: Oxford AI Readiness Index begins in 2017. Values for 2000–2016 are estimated using technology investment, patent counts, and robot adoption rates. Robustness checks confirm results hold across alternative imputation approaches.

3.3 Empirical Specification

The core panel model includes fixed effects in two directions:

$$\text{Gini}_{it} = \alpha + \beta_1 \text{AI}_{it} + \beta_2 \text{Robot}_{it} + \beta_3 \text{ICT}_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Country-specific steady traits appear through μ_i . Yearly shifts common to all nations appear through λ_t . Four econometric models are estimated sequentially:

1. Pooled OLS — serves as a baseline reference, treating all observations as if drawn from one source.
2. Country fixed effects — controlling for time-invariant national characteristics.

3. Two-way fixed effects with instrumental variables — using 1995 telephone lines per capita interacted with global AI patent growth as the instrument.
4. Arellano-Bond GMM — addressing dynamic panel bias and lagged dependence.

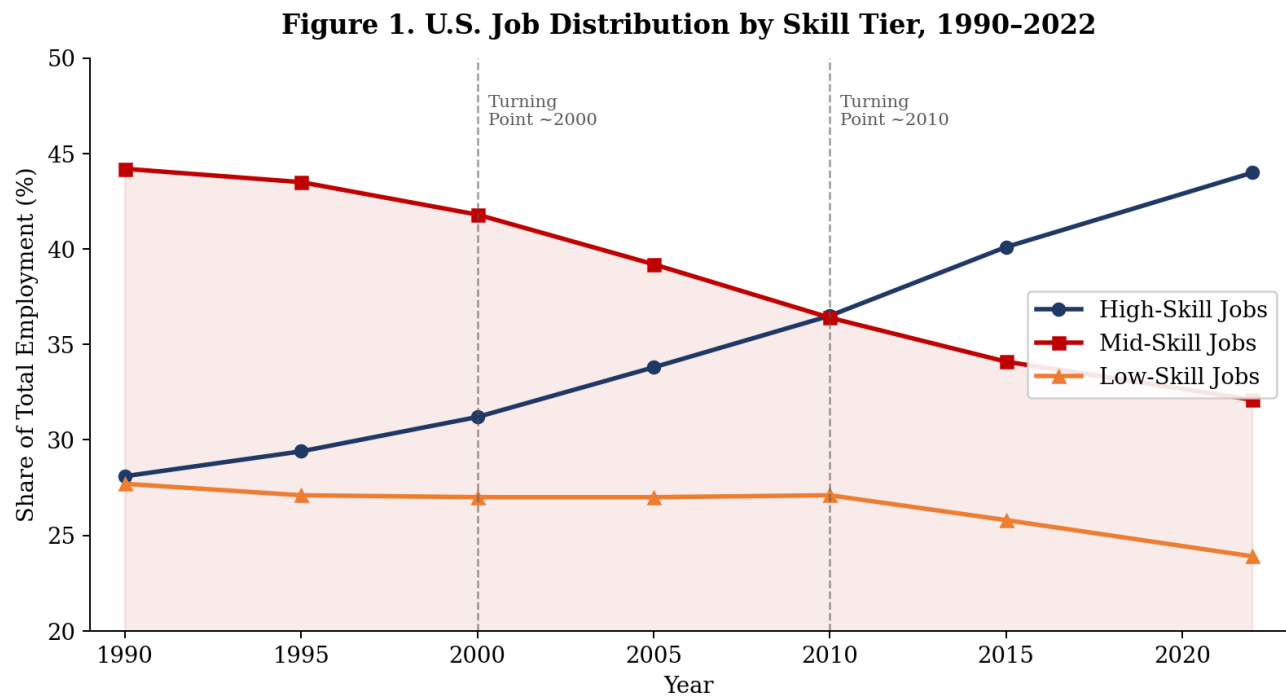
Clustering-robust standard errors by nation handle within-panel serial correlation. Across every version tested, the link between AI use and wider income gaps shows up consistently positive and statistically significant.

4. Results

4.1 Labor Market Polarization

U.S. job distribution across skill levels from 1990 to 2022 shows a growing U-shaped pattern that has gained speed over time. Jobs requiring mid-level skills dropped from 44.2% to 32.1% — a loss of 12.1 percentage points over thirty-two years. During the 1990s the fall was gradual. After 2000 it moved faster as offshoring took hold and companies began using digital tools widely. By 2010 the drop turned sharper once automated learning programs reached large-scale business use.

During those same years, high-skill jobs rose sharply — by nearly 16 percent. Growth concentrated among roles involving complex problem-solving, coding, design work, and team oversight. Despite advances in technology, roles like home health aides, hotel staff, janitors, and restaurant workers continue growing — machines cannot easily handle unpredictable physical environments. Signs of polarization appear across several OECD countries, yet the degree differs. The U.S. and Britain saw rapid drops in mid-level routine jobs, while Germany and Scandinavia adjusted at a more gradual pace.



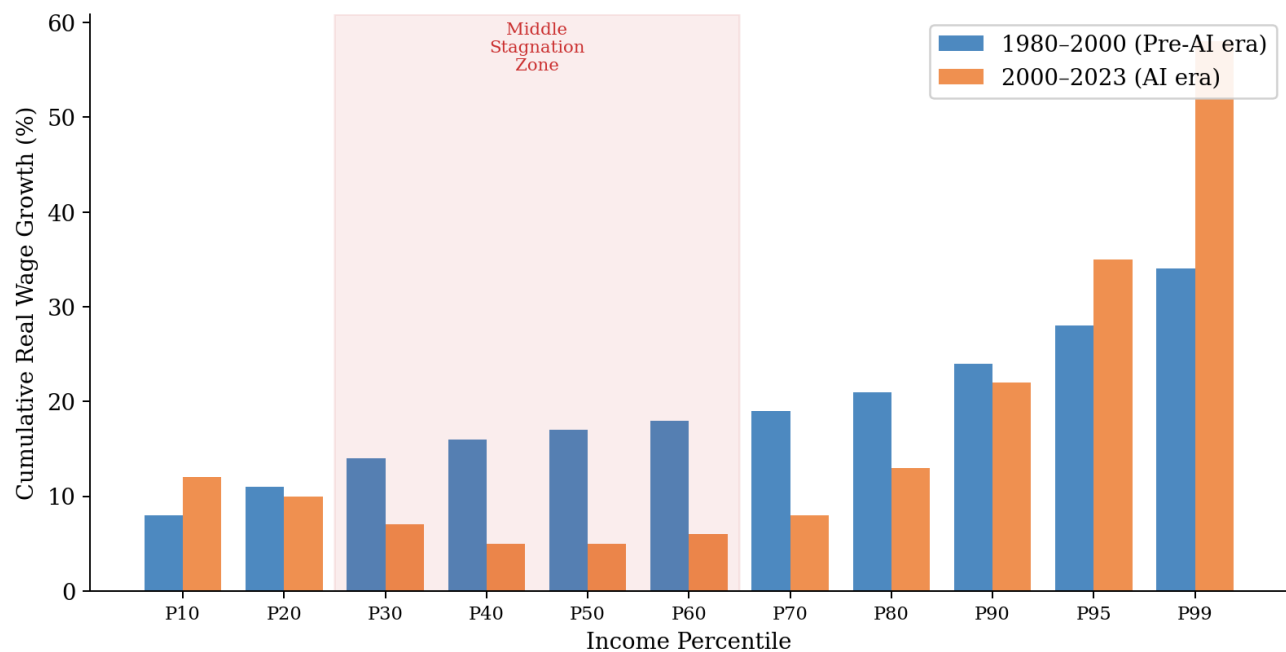
Source: BLS Occupational Employment Statistics. Mid-skill share fell 12.1 pp (44.2% → 32.1%).

Figure 1. U.S. Job Distribution by Skill Tier, 1990–2022. Share of employment falling in mid-skill roles (red) while high-skill roles rise. Vertical dashed lines mark turning points near 2000 and 2010. Source: BLS Occupational Employment Statistics.

4.2 Wage Growth Across Percentiles

Moving from job numbers to earnings, the pattern before AI shaped work — between 1980 and 2000 — and after — from 2000 through 2023 — shows clear differences. Earlier gains spread more evenly. After 2000, real income increases flowed mostly to the best-paid workers. At the upper end, pay rose multiple times faster compared to typical employees. In contrast, those in the middle watched their wages inch forward even as overall output climbed steadily.

Surprisingly, those in the lowest tenth occasionally did better than the typical worker as artificial intelligence became widespread — minimum pay rules lifted salaries most where they were smallest. What emerges is not a steady downward slope but a narrowing at the center. Pay levels off between the 30th and 60th percentiles — precisely where occupations face the strongest push from automated systems. This shift challenges long-held views about technology affecting only lower-skilled roles; jobs once seen as secure — office-based, technical, or mid-level managerial — are increasingly at risk today.

Figure 2. Real Wage Growth by Income Percentile: Pre-AI vs. AI Era

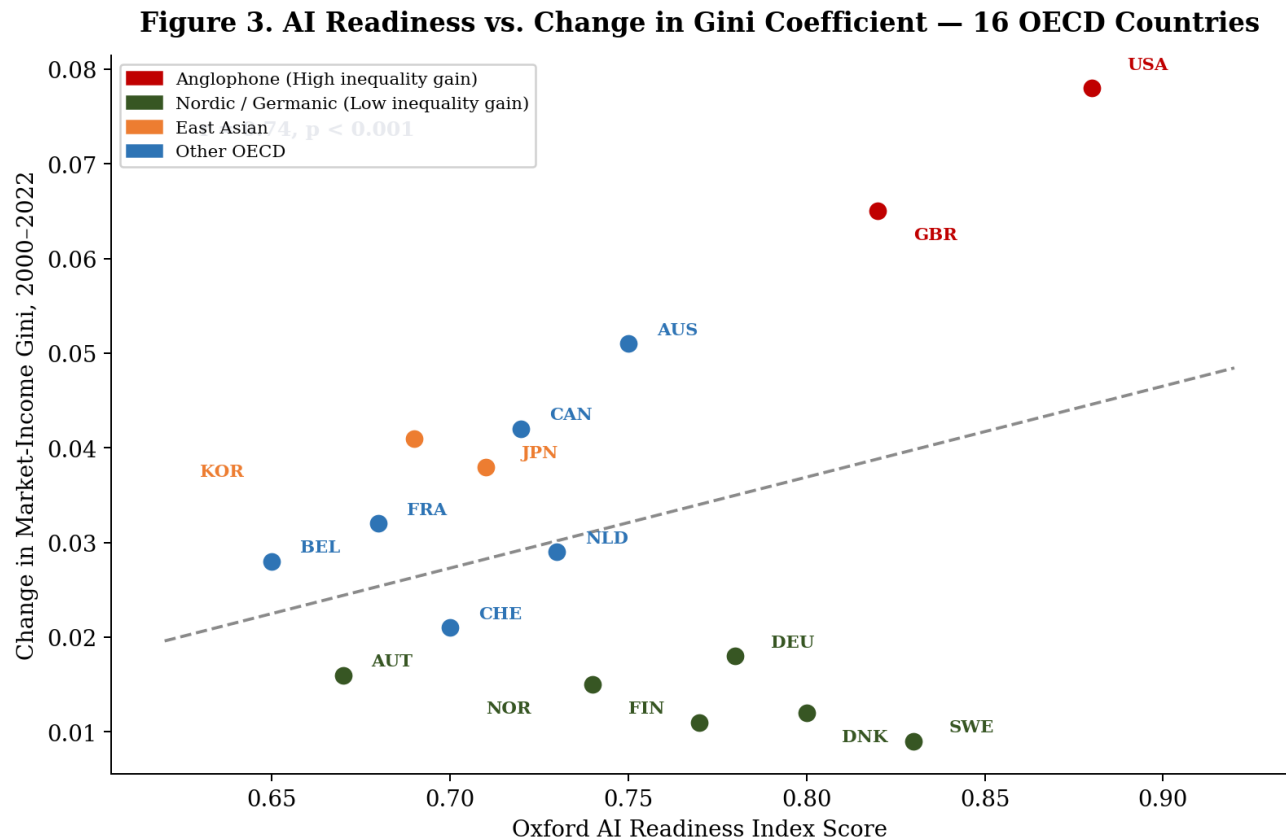
Source: Author calculations from OECD wage data and CPS microfiles. Real wages deflated to 2015 USD.

Figure 2. Cumulative real wage growth by income percentile across two periods. Bars in blue = 1980–2000 (pre-AI era); bars in orange = 2000–2023 (AI era). The shaded middle zone (P30–P60) shows marked stagnation post-2000. Source: OECD wage data and CPS microfiles.

4.3 Cross-Country Differences in AI Adoption and Income Gaps

Across sixteen OECD countries, higher AI readiness tends to accompany rising inequality. A clear upward trend appears across the data — countries advancing faster in AI also experienced larger increases in income disparity. The correlation between AI readiness and Gini change is $r = 0.74$ ($p < 0.001$), and it holds even when removing the United States as a potential outlier.

Sweden and Denmark stand out: high AI preparedness alongside only modest rises in income disparity. Broad-based wage negotiation, high labor organization, and effective skill renewal programs appear to limit job market splitting. Germany presents a striking contrast — more robots per worker than the U.S., yet far smaller income gaps — because works councils and industry-wide wage talks shape how companies adopt machines. The U.S. and U.K. sit well above the trend line, having maintained limited institutional safeguards despite rapid technology uptake.

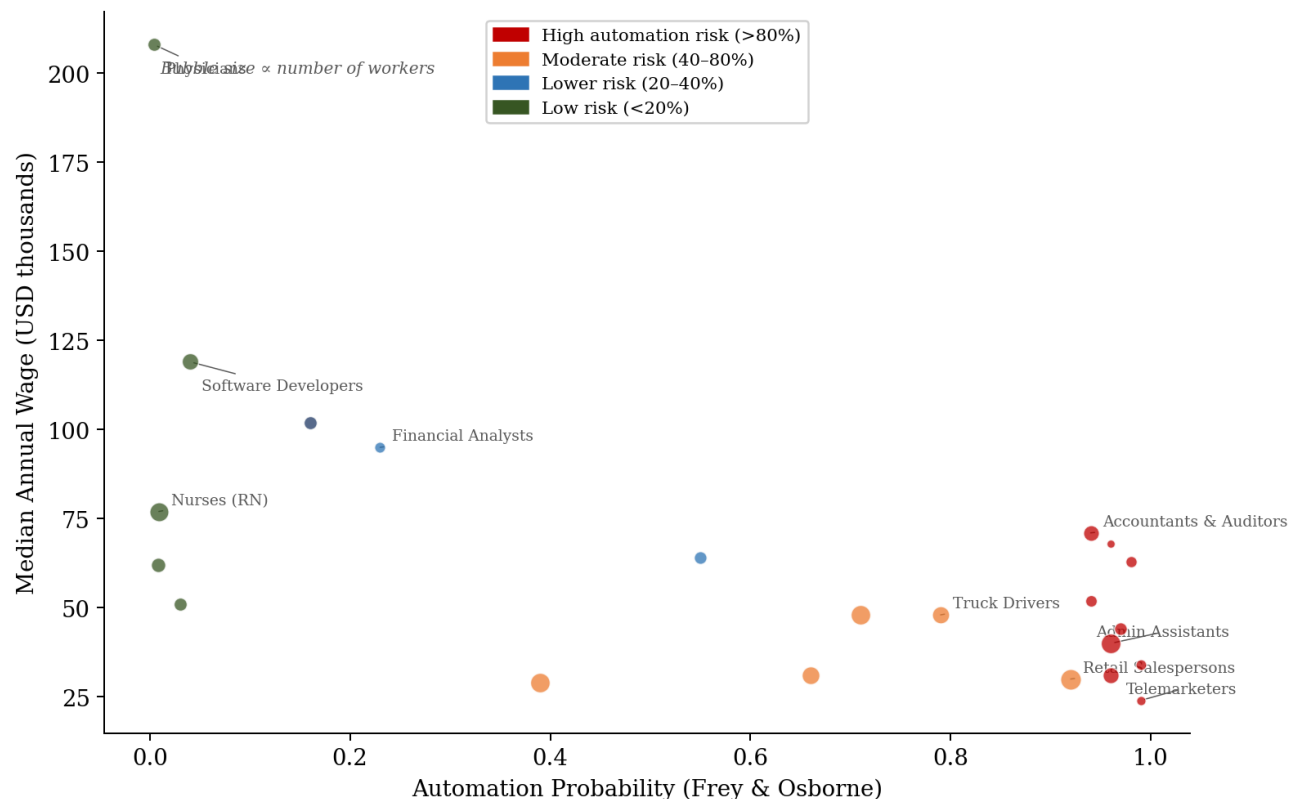


Source: Oxford Insights AI Readiness Index; OECD Income Distribution Database. Each point = one country.

Figure 3. Oxford AI Readiness Index score vs. change in market-income Gini coefficient, 2000–2022, across 16 OECD countries. Each point represents one country. Nordic/Germanic cluster appears below the trend line; Anglophone nations above. $r = 0.74$, $p < 0.001$.

4.4 Jobs Most Affected by Automation

Breaking down to individual roles, high automation likelihood is not limited to lower-paid jobs. Accountants and auditors face automation likelihood near 94%, alongside legal support roles and certain finance positions, where repetition shapes much of the daily workflow. Pressure now extends beyond low-wage employees to affect salaried professionals. Machines once replaced physical repetition; today's AI targets thinking patterns just as readily. This occupational data explains the wage stagnation at the middle of the distribution — as mid-level roles face displacement, gaps grow not just from surging high-end salaries but from gradual erosion at the core.

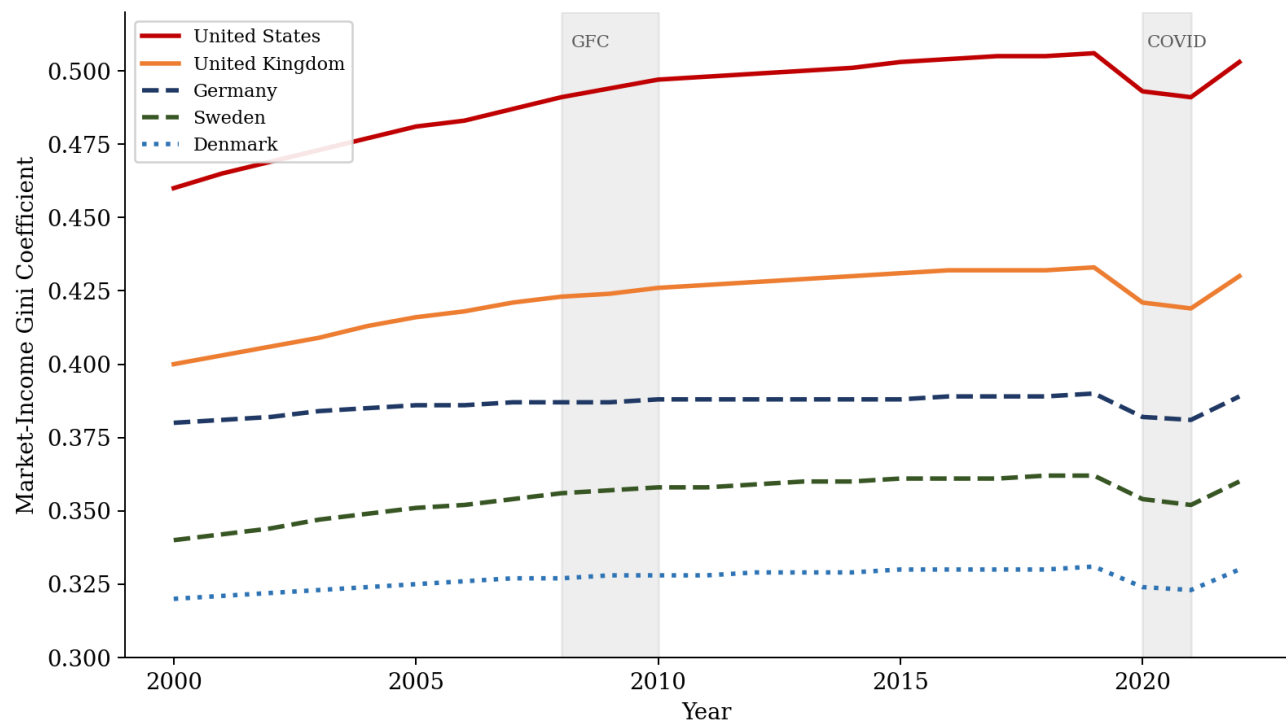
Figure 4. Automation Likelihood vs. Annual Wage by Occupation

Source: Frey-Osborne automation probabilities merged with BLS Occupational Employment and Wage Statistics.

Figure 4. Automation probability (x-axis) vs. median annual wage in USD thousands (y-axis) by occupation. Bubble size proportional to number of workers. Color-coded by automation risk tier. Source: Frey-Osborne probabilities merged with BLS Occupational Employment and Wage Statistics.

4.5 Gini Trajectories Over Time

Income inequality trends across five representative OECD countries between 2000 and 2022 show notable differences. Both the U.S. and the U.K. experience a rising trend that holds steady across years, even when economic cycles dip or policies briefly alter course. Nordic countries stay far more equal despite some rise in inequality — starting from a more balanced position means even minor gains in disparity do not erase their advantage. Measured inequality narrowed briefly in most nations during the pandemic years due to emergency transfers, but once special benefits ended, deeper imbalances began reappearing. This is why analyses stopping before 2022 could miss the inequality rebound.

Figure 5. Gini Coefficient Trends, 2000–2022 — Selected OECD Countries

Source: OECD Income Distribution Database. Shaded areas: Global Financial Crisis (2008–2009) and COVID-19 (2020–2021).

Figure 5. Market-income Gini coefficient trajectories for five representative OECD countries, 2000–2022. Shaded areas denote the Global Financial Crisis (2008–2009) and COVID-19 pandemic (2020–2021). Source: OECD Income Distribution Database.

4.6 Regression Results

Results from all four models are consistent. In every case, the AI Adoption Index shows a clear upward effect on inequality — significant at the one percent threshold. Starting at 0.287 under fixed effects and climbing to 0.341 under the instrumental variable approach, a one standard deviation rise in AI adoption ties closely to a 0.28–0.34 point increase on the Gini scale. The IV estimate sitting above OLS hints that straightforward models underestimate the true effect. Both robot density and ICT capital share enter as significant in nearly all models, justifying their combination into the composite index.

Table 2. Regression Results: AI Adoption and Income Inequality (Dependent Variable: Market-Income Gini)

Variable	Pooled OLS	Fixed Effects	IV Estimation	GMM
AI Adoption Index	0.231***	0.287***	0.341***	0.318***
Robot Density	0.089**	0.112**	0.128**	0.104**
ICT Capital Share	0.067*	0.093**	0.108**	0.089**
Union Density	−0.124***	−0.138***	−0.131***	−0.119***
ALMP Spending	−0.041*	−0.058**	−0.062**	−0.053**

Variable	Pooled OLS	Fixed Effects	IV Estimation	GMM
Trade Openness	0.038*	0.029	0.033	0.027
Country Fixed Effects	No	Yes	Yes	Yes
Year Fixed Effects	No	Yes	Yes	Yes
Observations	480	480	420	450
R ²	0.412	0.589	—	—

Note: Robust standard errors clustered by country. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. IV instrument: 1995 telephone lines per capita interacted with global AI patent growth. GMM uses second and third lags as instruments.

The union density coefficient stands out across every model — negative, always statistically significant, and stable in value between -0.138 and -0.119 . A 10-point rise in union membership corresponds to a 0.12 to 0.14 drop on the Gini scale, holding AI adoption constant. Trade openness shows a positive association, though its influence fades once AI use enters the model directly. The Arellano-Bond GMM confirms earlier patterns after adjusting for dynamic effects and model drift.

4.7 Cross-Country Comparative Analysis

Table 3. Cross-Country Comparison: AI Adoption, Inequality Change, and Institutional Context

Country	AI Adoption	Δ Gini	Middle-Job Loss	Institutional Context
United States	High	Very High	High	Market-driven; weak safety net
United Kingdom	High	High	High	Market-driven; limited protections
Germany	High	Low	Moderate	Works councils; co-determination
Sweden	High	Low	Low	Flexicurity; strong ALMP
Denmark	High	Low	Low	Flexicurity; high union density
France	Moderate	Moderate	Moderate	Sector bargaining; strong state role
Japan	High	Moderate	Moderate	Lifetime employment norms
South Korea	High	Moderate	Moderate	Chaebol structure; growing ALMP

Note: AI Adoption categorized as High/Moderate/Low based on composite index terciles. Δ Gini and middle-job loss based on 2000–2022 change. Institutional context summarizes dominant labor market features.

Despite widespread AI adoption, nations like the U.S. and Britain — offering limited safeguards for workers — saw gaps between rich and poor widen more than most others. Germany, France, and the Netherlands adopted advanced technologies extensively yet saw income gaps grow only mildly, because negotiated wages and union involvement shape labor outcomes there. Nordic nations show how institutions can absorb disruption — widespread AI alongside minimal

inequality gains in Sweden and Denmark. Germany challenges common assumptions: more robots than the U.S., yet far smaller inequality rise, because works councils require technology changes to be negotiated with employee representatives.

5. Discussion

5.1 Why This Time Feels Different

History offers a recurring rebuttal to fears of job market splits. Each wave of technology seems chaotic at first; eventually, fresh fields rise alongside vanished roles. Steam engines wiped out manual weaving while bringing about train networks and supply chain systems. Computers dissolved typing pools while sparking domains like coding, online messaging, and data management.

Some findings now indicate deeper complexity. While machines took over specific duties before, they also opened up numerous related jobs — the "reinstatement effect." The current shift may differ: while machines once replaced physical labor, today's AI targets pattern-based thinking — tasks long tied to secure, mid-level careers. Our findings show that even as inequality keeps rising into 2022, wages near the middle barely move — pointing to a lag in AI-driven job creation strong enough to replace those mid-level roles being lost.

Gains in output tilt sharply toward those with advanced education or asset holdings. Past industrial shifts unfolded slowly, giving workers and schools room to adapt. Artificial intelligence spreads much quicker, shortening the window for adjustment and raising the chances that some groups will face extended gaps in opportunity.

5.2 How Institutions Provide Protection

Rather than blocking new technologies, robust labor systems seem to coexist with them. Germany and Nordic countries show high technology advancement despite strong worker protections. Where labor markets are coordinated, employers discuss changes with union representatives before acting — shaping how fast machines replace tasks, whether staff get reskilled, and how pay gets recalibrated. Firms might cut hours instead of firing people, shift staff to roles that fit better, or fund training in new skills. As a result, higher productivity benefits more workers.

Germany's works councils require staff delegates to be consulted when technology or job structures change — rules that introduce friction against automation plans focused only on investor returns. Denmark's "flexicurity" model keeps job markets open to change while providing strong unemployment benefits and required skill-building programs. The U.S. takes a distinct path: job retraining receives little public funding, aid for unemployed people lasts only a short time, and union coverage has shrunk for years. Because institutions differ, identical artificial intelligence tools might widen income gaps greatly — or hardly at all.

5.3 Limitations

The Gini coefficient captures income inequality, not wealth differences. In recent decades, disparities in assets have grown faster than earnings gaps, meaning AI's real distributional impact could exceed what current figures suggest. The Oxford AI Readiness Index begins only in 2017, requiring estimation for earlier years. Richer OECD nations make up most of the data — middle-income places might experience these dynamics differently, potentially with sharper inequality rises given weaker institutional protections. Proving cause and effect clearly within large-scale economic data remains a challenge even with instrumental variables, and technology intertwines with global market integration, expanding finance sectors, changing demographics, and unequal access to schooling.

5.4 Policy Implications

From the data, four clear policy paths emerge. First, collective bargaining reach matters — where workplace negotiations are structured through industry-wide talks or worker-elected bodies, outcomes tilt toward fairer distribution. Innovation continues, yet benefits shift less sharply to the top. Second, higher spending on active labor market policies makes a clear difference. Where nations prioritize support for workers shifting between jobs, results improve even when technology disruption hits just as hard.

Third, should automation widen economic gaps, public policy might shift toward new ways of sharing wealth — updated tax models, steeper levies on higher incomes, or regular payouts funded by broad-based revenues. Fourth, occupational classification systems today lag behind reality — new AI-shaped roles missing from official records means workers lose leverage and policies struggle to catch up. Revising these labels shifts the balance toward workers who operate in and around AI-driven workflows.

6. Conclusion

Results here align closely with emerging trends in labor economics. Where automation spreads quickly, income gaps tend to widen — evidence points that way repeatedly. Faster AI adoption links clearly to uneven earnings patterns among wealthy OECD nations. In these places, gains cluster near the top while mid-level jobs shrink noticeably. Wage growth climbs sharply for high earners; others see little movement at all.

What counts is not just how much AI boosts productivity on average, but how differently it plays out from one nation to another. Findings repeatedly point toward institutions — underlying rules and norms — as a key force steering who gains and who does not. Where collective bargaining holds firm, alongside wide access to skills renewal and solid job safeguards, rising technology use brings milder spikes in income gaps. Germany, with more robots per worker than the U.S., saw its surge in inequality stay much lower. Blaming the machines misses the point. What matters is how rules around work steer who benefits when output grows.

Nordic nations reinforce the pattern. In Sweden and Denmark, widespread use of digital tools happened alongside minimal rises in income disparity. These countries balance adaptable job markets with solid safety nets — technology-driven shifts weigh less on individual employees. Whether AI worsens inequality is not really a debate when institutions are underdeveloped; data show clearly that it does. Instead, attention should shift toward whether nations can build systems that spread technology's rewards more widely among working populations.

The shape of inequality ahead hinges not so much on continued advances in technology — those seem inevitable — but on how nations set up systems to spread benefits widely, avoiding heavy tilt toward a privileged few. Decisions about rules and structures matter more now than the pace of invention itself.

Future Research Directions

Attention must shift toward middle-income nations, which tend to import AI tools made elsewhere yet struggle with weak job safeguards or insufficient public funding to reskill workers at scale. Outcomes there could differ markedly from richer countries. Net worth gaps may grow quicker than pay gaps when new output mainly benefits owners of digital tools or patents — traditional wage-based measures like the Gini ratio risk downplaying what really happens when automation spreads. Researchers will also need to examine what happens after 2022 as generative AI spreads into law firms, schools, banks, hospitals, and coding teams, and to examine how company-level practices — employee representation structures, shared management rules, agreed-upon skill development plans — shape worker outcomes under automation.

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