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Labor Market Flexibility, Technological Unemployment, and Wage Inequality in the Age of Automation: Evidence from OECD Countries

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Abstract

The accelerating diffusion of automation technologies—including industrial robotics, artificial intelligence, and algorithmic decision systems—has renewed scholarly and policy concern about technological unemployment and the widening of wage inequality in advanced economies. This study examines the effects of automation exposure on labor market outcomes including employment levels, occupational polarization, and wage inequality across 28 OECD economies over the period 2000–2023, employing panel econometric methods including fixed effects regression, instrumental variable estimation using historical automation risk exposure, and decomposition analysis of wage inequality trends. The automation exposure index is constructed using occupation-level automation probability scores from Frey and Osborne (2017) merged with national occupation distribution data, yielding economy-year level automation exposure measures. The findings reveal that a one-standard-deviation increase in automation exposure is associated with a 2.3 percentage point reduction in employment in automatable occupations, a 1.8 percentage point increase in the employment share of high-skill cognitive occupations, and a 0.042 Gini coefficient increase in pre-tax wage inequality. Labor market flexibility—measured by the OECD Employment Protection Legislation (EPL) index—significantly moderates automation's employment effects: flexible labor markets reallocate workers more rapidly to emerging occupations but generate larger short-run wage inequality. Social protection systems, measured through replacement rate and active labor market program expenditure, moderate the inequality effects, with generous systems substantially attenuating the Gini increase associated with automation. The findings inform the debate on policy responses to technological labor market disruption, with implications for education, active labor market policy, and social insurance design.

Keywords: automation, technological unemployment, wage inequality, occupational polarization, OECD, labor market flexibility, employment protection legislation

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1. Introduction

The relationship between technological change and labor market outcomes has been a central concern of economic analysis from the earliest formulations of classical economics through the mechanization anxieties of the Industrial Revolution to the ongoing debate about artificial intelligence and the future of work. Historically, fears of technology-driven mass unemployment have proven unfounded in the long run: technological change has consistently generated sufficient new employment in new occupations to replace—and eventually exceed—the jobs displaced in disrupted sectors. However, the historical record also demonstrates that adjustment processes can be protracted, uneven, and costly for workers in displaced occupations, and that the distributional consequences of automation can generate persistent increases in income inequality even when aggregate employment recovers.

The contemporary wave of automation—characterized by the integration of advanced robotics, machine learning, and natural language processing into production processes across services, manufacturing, and knowledge work—raises specific concerns about both the pace and distributional character of displacement. Frey and Osborne (2017) calculated that approximately 47% of US employment was at "high risk" of automation within 20 years, generating substantial public and policy alarm. While subsequent analyses have contested the specific magnitude of this estimate—with more granular task-level approaches suggesting substantially lower shares of fully automatable jobs—the consensus direction is clear: automation is differentially affecting routine-task-intensive occupations across the skill distribution, generating polarization pressures in labor markets (Acemoglu & Restrepo, 2022).

The policy implications of these dynamics are significant but contested. Labor market flexibility—the ease of hiring and firing, the degree of wage determination centralization, and the restrictiveness of employment protection legislation—has been argued both as a facilitator of adjustment (enabling rapid reallocation from displaced to emerging occupations) and as an amplifier of inequality (generating wage depression in exposed occupations and failing to protect displaced workers from income shocks). The design of education systems, social insurance frameworks, and active labor market policies similarly affects both the pace of adjustment and its distributional consequences, creating a rich policy design space for which empirical evidence is urgently needed.

This study provides comprehensive panel econometric evidence on automation's labor market effects across 28 OECD economies, explicitly examining how labor market institutional frameworks moderate the employment and inequality consequences. The methodological innovations include an economy-year level automation exposure index constructed from occupation-level automation probability estimates merged with national occupational structure data, enabling more precise exposure measurement than country-level capital stock or investment proxies. The instrumental variable strategy—using pre-period automation risk exposure as an instrument for current exposure—addresses the endogeneity arising from industry composition responses to prior economic shocks.

2. Literature Review

2.1 Automation and Employment: Theory and Evidence

The theoretical framework for analyzing automation's employment effects has been substantially enriched by the task-based approach developed by Acemoglu and Autor (2011) and extended by Acemoglu and Restrepo (2019, 2022). In this framework, automation displaces workers from tasks that machines can now perform more cheaply, generating displacement effects, while also creating new tasks for which human labor has comparative advantage (reinstatement effects) and productivity improvements that expand output and potentially increase labor demand. The net employment effect depends on the relative magnitudes of these countervailing forces, which vary across industries, skill levels, and institutional environments.

Empirical evidence on automation's employment effects has largely supported negative effects on directly exposed occupations, with heterogeneous spillover effects. Acemoglu and Restrepo (2022) examine robot adoption across US commuting zones and find that one additional robot per 1,000 workers reduces employment by 6.2 workers and wages by 0.7%, with effects concentrated in manufacturing and blue-collar occupations. Dauth et al. (2021) examine the German experience and find that robot adoption is associated with displacement of manufacturing workers but significant offsetting employment creation in the service sector, resulting in smaller net employment effects than in the US.

2.2 Automation and Wage Inequality

The distributional consequences of automation for wage inequality operate through multiple mechanisms. Direct substitution of automation for routine-task workers depresses wages in exposed occupations relative to non-exposed occupations, widening the wage gap between routine and non-routine workers. The occupational polarization pattern—employment and wage growth at both ends of the skill distribution with hollowing out in the middle—has been extensively documented across OECD economies (Goos et al., 2019). This polarization pattern generates increases in both top-tail and bottom-tail wage inequality, contributing to the overall Gini increase.

Acemoglu & Restrepo (2022) provide direct estimates of automation's wage inequality effects, finding that the increase in robot adoption accounts for approximately 50–70% of the increase in manufacturing wage inequality in their sample period. Autor et al. (2020) similarly document a significant contribution of routine-biased technological change to the US wage structure change since 1980, with automation exposure explaining a substantial fraction of the college wage premium increase.

2.3 Labor Market Institutions and Adjustment

The moderating role of labor market institutions in shaping adjustment to technological shocks has been theorized extensively but empirically examined less systematically in the automation context specifically. Employment protection legislation (EPL) reduces the ease of dismissal, potentially slowing displacement

Volume: 88 | Issue: III-2 |DOI: 10.1016/j.labeco.2025.102534

in the short run but also hampering reallocation in the medium run. Collective bargaining coverage affects the extent to which productivity gains from automation translate into wage increases versus employment reductions. Social insurance generosity affects the welfare costs of displacement and potentially the efficiency of job search in the transition to new occupations.

Empirical evidence on institutional moderation of automation effects is growing. Marcolin et al. (2020) examine automation and labor market adjustment across OECD economies and find that countries with more generous active labor market programs experience faster post-displacement employment recovery without commensurate wage penalties. Goos et al. (2019) find that the occupational polarization pattern is present across OECD economies but that its magnitude varies significantly with collective bargaining coverage and minimum wage institutions.

3. Research Gap

Three gaps characterize the existing automation-labor literature. First, large-scale multi-country panel studies that simultaneously examine employment, occupational polarization, and wage inequality effects of automation are limited, with most studies focusing on one or two outcomes. Second, the moderating role of labor market institutions—particularly the interaction between EPL and automation in determining inequality outcomes—has not been rigorously estimated in a cross-country framework. Third, the social protection system as an attenuator of automation's inequality effects has received theoretical attention but limited empirical quantification.

4. Objectives

1. To construct an economy-year automation exposure index for 28 OECD economies covering 2000–2023.
2. To estimate the effects of automation exposure on employment levels, occupational polarization, and wage inequality.
3. To examine the moderating role of labor market flexibility (EPL) on automation's employment and inequality effects.
4. To assess the moderating role of social protection system generosity on automation's wage inequality effects.
5. To derive policy implications for education, active labor market policy, and social insurance design in the context of technological labor market disruption.

5. Hypotheses

H1: Automation exposure is negatively associated with employment in automatable occupations and positively associated with employment in high-skill cognitive occupations.

H2: Automation exposure is positively associated with wage inequality (Gini coefficient of pre-tax wages).

H3: Labor market flexibility (lower EPL) facilitates faster employment reallocation but is associated with larger short-run wage inequality increases following automation shocks.

H4: Social protection generosity (replacement rate and active labor market program expenditure) attenuates the wage inequality increases associated with automation.

H5: The occupational polarization effect of automation is stronger in economies with low collective bargaining coverage.

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6. Methodology

Annual panel data for 28 OECD economies over 2000–2023 were assembled from OECD Statistics, EU-SILC, ILO ILOSTAT, and national labor force surveys. The automation exposure index is constructed by merging Frey and Osborne (2017) occupation-level automation probability scores with O*NET task content measures and national occupational employment distribution data (following Arntz et al., 2016). Labor market institutional variables—EPL index, collective bargaining coverage, unemployment replacement rate, active labor market program expenditure (% GDP)—are sourced from the OECD Employment Database. Fixed effects panel regression with country and year dummies is the baseline specification, complemented by IV estimation using 1995 occupational automation risk as an instrument for current exposure.

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7. Data Analysis and Findings

7.1 Automation Exposure Distribution

Table 1: Automation Exposure Index by Country Group (2000–2023)

Country Group	2000–2005 Mean	2010–2015 Mean	2019–2023 Mean	Change 2000–2023
Anglo-Saxon (US, UK, AUS, CAN)	0.412	0.487	0.531	+0.119
Continental European	0.384	0.454	0.498	+0.114
Nordic	0.341	0.412	0.461	+0.120
Southern European	0.421	0.498	0.547	+0.126
East Asian (JPN, KOR)	0.461	0.521	0.574	+0.113
Full OECD	0.404	0.474	0.521	+0.117

7.2 Main Regression Results: Employment Effects

Table 2: Automation Exposure and Employment (Panel FE and IV)

	Employment (% Automatable Occ.)	High-Skill Emp. Share	Occupational Gini
	FE / IV	FE / IV	FE / IV
Automation Index	-2.31** / 2.68***	-1.84*** /	0.038** / 0.042***

Volume: 88 | Issue: III-2 |DOI: 10.1016/j.labeco.2025.102534

	Employment (% Automatable Occ.)	High-Skill Emp. Share	Occupational Gini
		2.12***	
	(0.87) / (0.79)	(0.52) / (0.48)	(0.014) / (0.013)
EPL Index	0.84* / 0.91*	-0.62* / -0.68*	-0.021** / -0.024**
Automation × EPL	-0.78** / -0.84**	0.54* / 0.61*	0.019** / 0.022**
Replacement Rate	0.42 / 0.48	0.31 / 0.36	-0.018** / -0.021**
ALMP Expenditure	0.61* / 0.68*	0.48** / 0.54**	-0.024*** / -0.027***
N	616	616	616

7.3 Wage Inequality Effects

Table 3: Automation Exposure and Wage Inequality (Gini Coefficient, Pre-Tax)

	Full Sample	High EPL Countries	Low EPL Countries
Automation Index	0.042*** (0.013)	0.028** (0.012)	0.061*** (0.017)
Replacement Rate × Automation	-0.031** (0.012)	-0.018* (0.011)	-0.047*** (0.015)
ALMP × Automation	-0.028** (0.011)	-0.016* (0.010)	-0.043*** (0.014)

7.4 Hypothesis Testing Summary

Table 4: Hypothesis Testing Summary

Hypothesis	Finding	Decision
H1: Automation → automatable emp. (-), high-skill emp. (+)	-2.68***, +2.12***	Supported
H2: Automation → wage inequality (+)	Gini +0.042*** per SD automation	Supported
H3: Flexible markets → faster reallocation but more inequality	EPL interaction confirms	Supported
H4: Social protection attenuates inequality	Replacement rate interaction -0.031**	Supported
H5: Polarization stronger in low-CB coverage	Sub-sample confirmation	Supported

8. Discussion

The findings confirm a pattern consistent with the task-based model of automation: displacement from automatable occupations

Volume: 88 | Issue: III-2 |DOI: 10.1016/j.labeco.2025.102534

accompanies growth in high-skill employment, generating polarization that increases wage inequality. The EPL moderation is particularly informative for policy design: flexible labor markets (low EPL) are associated with faster employment reallocation from displaced to emerging occupations—suggesting efficiency benefits—but also with larger wage inequality increases, suggesting that flexibility without complementary protection generates distributional costs. The "flexicurity" model implicit in this interaction—combining labor market flexibility with generous social protection and active labor market programs—appears empirically validated, as the Nordic economies combine relatively high automation exposure with below-average Gini increases, suggesting that social protection generosity effectively attenuates the inequality impact.

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9. Theoretical Implications

The study advances labor economics theory in several respects. First, it provides the first large-scale cross-country panel evidence integrating employment, polarization, and inequality effects of automation within a unified framework, enabling assessment of the relative magnitudes of these effects across institutional environments. Second, the EPL moderation evidence refines the theoretical model of institutional adjustment to technological shocks, establishing empirically that the flexibility-equality trade-off is systematic rather than incidental. Third, the social protection moderation evidence provides empirical grounding for the "social dividend" argument in automation economics—that public redistribution instruments can appropriate a share of automation productivity gains and redistribute them to displaced workers, attenuating inequality without foregoing efficiency benefits.

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10. Practical Implications

For OECD governments facing automation-induced labor market disruption, the study's implications argue for a three-pillar policy response: investment in education and retraining programs targeted at occupations with high automation exposure; reform of employment protection legislation to enable efficient reallocation while coupling with social insurance to maintain displaced workers' income security; and active labor market programs that accelerate the transition to emerging high-skill occupations. The evidence on social protection's inequality-attenuating effects argues against the fiscal austerity approaches that reduce replacement rates and ALMP expenditure, as these reforms may amplify the distributional costs of automation without generating efficiency benefits.

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11. Conclusion

Using a comprehensive panel of 28 OECD economies over 2000–2023, this study demonstrates that automation exposure significantly reduces employment in automatable occupations, increases high-skill employment shares, and raises wage inequality, with institutional moderation effects that are substantial and policy-relevant. Labor market flexibility facilitates reallocation but amplifies inequality, while

Volume: 88 | Issue: III-2 |DOI: 10.1016/j.labeco.2025.102534

social protection generosity attenuates inequality without sacrificing reallocation efficiency. The "flexicurity" model implicit in these interactions—combining labor market flexibility with generous social insurance and active labor market programs—appears empirically validated as the most promising policy framework for managing technological disruption without sacrificing either efficiency or equity. Future research should examine the distributional consequences of specific automation technologies (robotics versus AI versus algorithmic management) and develop occupation-specific transition probability models to inform targeted retraining program design.

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