Available Online: 18 April 2025 DOI: 10.54254/3657-4300/1/2025004

AI Adoption and Labor Market Polarization: A Game-Theoretic Model Based on Occupational Substitution Elasticity

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Abstract. This paper explores the dynamics of AI adoption and its impact on labor market polarization through a game-theoretic model incorporating occupational substitution elasticity. By modeling the strategic interaction between firms and heterogeneous labor groups, we demonstrate how differences in substitution elasticity between high-skill, middle-skill, and low-skill occupations lead to divergent outcomes in wage distribution, employment, and firm profitability. The results reveal that when the elasticity of substitution for middle-skill jobs is high, firms have stronger incentives to automate these roles, exacerbating labor market polarization. The findings provide a theoretical foundation to understand how technological advances—particularly in artificial intelligence—reshape labor structures, and suggest implications for education policy, labor regulation, and corporate strategy.

Keywords: AI adoption; labor market polarization; occupational substitution elasticity; game theory; automation; employment structure; wage inequality; technological unemployment

1. Introduction

1.1. Research Background

The rapid advancement of artificial intelligence (AI) technologies over the past decade has ushered in a new wave of technological disruption with far-reaching implications for labor markets. Unlike previous industrial revolutions, which largely automated manual or physical labor, contemporary AI systems are increasingly capable of replicating cognitive and even decision-making tasks. From generative language models to predictive maintenance systems and robotic process automation, the capacity of AI to perform tasks traditionally carried out by humans has expanded dramatically.

A growing body of empirical research highlights the asymmetric effects of this disruption, commonly referred to as labor market polarization. Middle-skill occupations—especially those involving routine tasks such as clerical work, assembly line operations, and data entry—have experienced significant displacement. For instance, Autor, Levy, and Murnane (2003) documented how computers substitute for routine tasks but complement abstract, non-routine cognitive work. Building on this, Goos, Manning, and Salomons (2014) found that the share of employment in mid-wage occupations has declined across OECD countries, while both high-wage professional jobs and low-wage service jobs have expanded.

This U-shaped employment shift has become a defining feature of contemporary labor market transformation.

The polarization phenomenon is particularly pronounced in sectors where AI systems offer clear productivity advantages. In manufacturing, robotic arms can now assemble products with speed and precision surpassing human labor. In finance and administration, machine learning models automate data analysis and fraud detection. Conversely, low-skill service jobs such as cleaning, caregiving, and food service remain resistant to full automation due to their non-routine and highly context-specific nature. Similarly, high-skill jobs in science, technology, engineering, and mathematics (STEM) often benefit from AI as a complement, enhancing productivity rather than replacing labor.

These developments raise important policy and theoretical questions: Why are middle-skill jobs disproportionately affected? What are the underlying mechanisms driving this shift? And how can economic models better capture the strategic interactions between firms adopting AI and the heterogeneous labor groups they employ?

1.2. Literature Review

The phenomenon of labor market polarization has been widely studied through the lens of skill-biased technological change (SBTC). According to this framework, technological progress disproportionately increases the demand for skilled labor, leading to rising wage inequality (Katz & Murphy, 1992). However, SBTC fails to fully account for the simultaneous growth in low-wage, low-skill employment, particularly in service sectors.

To address this, task-based models have gained traction in recent years. Seminal work by Acemoglu and Autor (2011) decomposes jobs into constituent tasks, allowing for a more granular analysis of automation. These models recognize that technologies substitute for routine tasks regardless of the overall skill level of the occupation, while non-routine tasks remain complementary. As a result, occupations with a high share of routine content—often found in middle-skill categories—are more susceptible to displacement.

Additionally, recent research by Acemoglu and Restrepo (2019, 2020) emphasizes the role of new task creation and reallocation of labor across sectors in moderating the effects of automation. However, while these models offer valuable insights, they often assume exogenous technological adoption decisions and do not fully explore the strategic nature of firm behavior. That is, firms are not passive adopters of technology but make rational, forward-looking choices based on cost, productivity, and competitive pressures.

A second limitation lies in the limited incorporation of heterogeneity in how different occupations interact with AI systems. Although empirical work increasingly documents occupation-specific exposure to automation risk (Frey & Osborne, 2017; Nedelkoska & Quintini, 2018), formal models often assume a binary substitution framework—jobs are either automatable or not—without modeling gradations of substitutability.

1.3. Research Contribution

This paper seeks to advance the theoretical understanding of AI-induced labor market polarization by introducing a game-theoretic model that incorporates occupational substitution elasticity. Substitution elasticity captures the ease with which AI can replace human labor in a given occupation, providing a more continuous and realistic measure than binary task classifications.

Our model conceptualizes a strategic game between firms and segmented labor markets—high-skill, middle-skill, and low-skill—each characterized by distinct substitution elasticities. Firms decide whether to adopt AI technologies based on the cost of automation, productivity gains, and the substitutability of labor. Workers respond through wage bargaining, skill acquisition, or exit from the labor market. The interaction generates equilibrium outcomes for wages, employment shares, and firm profits.

The key contributions of this study are threefold:

1. Theoretical innovation: By incorporating elasticities of occupational substitution, the model

provides a more refined understanding of why some jobs are more vulnerable to AI than others. Unlike prior models that treat technological substitution as a discrete outcome, we allow for strategic gradation in how firms replace or retain labor.

2. Strategic modeling: We integrate game theory to account for the mutual interdependence between firm decisions and labor responses. This fills a crucial gap in the literature by modeling firms not as passive actors but as strategic players optimizing across labor types and technological options.
3. Policy relevance: The model yields testable predictions about the conditions under which labor market polarization is most severe, and under which policies—such as wage subsidies, retraining programs, or AI taxes—may be most effective. It offers a framework for understanding how technological change, labor heterogeneity, and firm strategy jointly determine macro-level labor outcomes.

2. Theoretical Framework: A Game-Theoretic Model

This section introduces a stylized game-theoretic model to explain how firms and workers strategically interact in response to AI-driven technological change. At the heart of the model lies the concept of occupational substitution elasticity (σ), which captures the degree to which AI can replace human labor in specific tasks or jobs. By incorporating this heterogeneity, the model goes beyond binary task classifications and presents a nuanced depiction of labor market dynamics under automation.

2.1. Model Setup

The game is played between two main agents: firms and workers, who make interdependent decisions that ultimately determine labor allocation, wages, and technology adoption outcomes.

- Players:
  - Firms choose whether to adopt AI technologies and to what extent substitute human labor with automated systems.
  - Workers decide which occupational group to enter or exit, and whether to invest in reskilling to migrate between labor segments.
- Occupational Segments:
  We assume three types of labor markets—high-skill (H), middle-skill (M), and low-skill (L)—each with differing substitution elasticities. High-skill workers perform non-routine cognitive tasks, middle-skill workers perform routine tasks, and low-skill workers engage in manual, often non-automatable service work.
- Key Variables:
  - Occupational substitution elasticity (σ_i): reflects the cost-effective substitutability of AI for labor in occupation *i*.
  - Wages (w_i): equilibrium wage level for each occupation.
  - AI adoption cost (C): fixed and variable costs of implementing AI systems in firms.
  - Output function (Y): production as a function of labor input and AI capability.

Time is discrete. Each period, firms choose labor-AI input mixes, while workers observe expected wages and substitution risks and respond accordingly.

2.2. Firm's Decision Problem

Firms aim to maximize profits, taking into account the trade-offs between labor costs and the benefits of AI substitution. The representative firm's objective function can be written as:

$\pi = Y(H, M, L, A) - w\_H \cdot H - w\_M \cdot M - w\_L \cdot L - C(A)$

where:

- Y is the production function dependent on high-, middle-, and low-skill labor inputs, and AI capability (A);
- w_H, w_M, w_L are the wage rates for each skill segment;
- C(A) represents the cost of adopting and maintaining AI systems.

The substitution elasticity σ_i affects the marginal productivity of AI in replacing human input. For middle-skill jobs, where σ_M is assumed to be high, small improvements in AI capability significantly reduce the marginal cost of automation, making replacement more attractive.

Firms solve a constrained optimization problem:

Maximize π subject to:

$Y = F(L, A) = (\alpha_H \cdot H^\rho + \alpha_M \cdot (M^\rho + A^\rho/\sigma_M) + \alpha_L \cdot L^\rho)^{(1/\rho)}$

This CES (constant elasticity of substitution) production structure allows for analytical tractability and reflects the trade-off between labor and automation. Higher σ implies greater substitutability between M and A, increasing the likelihood of automation in that category.

2.3. Worker's Strategic Response

Workers observe prevailing wages and the elasticity-adjusted automation risk in each occupation and make strategic decisions accordingly. These include:

- Skill investment: Workers may choose to upskill or reskill, particularly if wages in high-skill jobs increase relative to middle-skill ones.
- Occupational migration: Individuals choose to move between occupational segments based on expected utility, which is a function of wage levels, probability of displacement, and training costs.

Let U_i be the expected utility from entering occupation *i*, defined as:

$U_i = (1 - R_i(\sigma_i)) \cdot w_i - \tau_i$

where:

- $R_i(\sigma_i)$ is the perceived risk of automation in occupation *i* based on substitution elasticity,
- τ_i is the fixed cost of entering (or retraining for) that occupation.

Workers choose the occupation that maximizes U_i. As σ_M rises, R_M increases, reducing the attractiveness of middle-skill work even if the nominal wage is high. Over time, we observe migration toward the high-skill and low-skill segments, reinforcing the empirical polarization trend.

2.4. Equilibrium Analysis

We now examine the Nash equilibrium of the game, defined as a strategy profile (firm AI adoption level and worker occupational choices) such that no player has an incentive to unilaterally deviate.

At equilibrium, the following conditions hold:

1. Firm optimality: Given worker distribution and wages, the firm's choice of labor-AI mix maximizes profit.
2. Worker optimality: Given wages and substitution elasticities, each worker chooses the occupation that maximizes expected utility.
3. Labor market clearing: Supply and demand in each occupation balance.

Let σ^* denote the threshold elasticity beyond which automation becomes the dominant strategy for firms:

If $\sigma_i > \sigma^*$, then $\partial\pi/\partial A_i > \partial\pi/\partial L_i$, implying automation displaces labor in that occupation.

From this, we derive the conditions for polarization:

- If $\sigma_M > \sigma^*$, middle-skill labor shrinks as firms automate and workers migrate.
- If $\sigma_L < \sigma^*$ and τ_L is low, low-skill labor expands due to displacement from the middle.
- If σ_H is low and w_H increases, high-skill occupations attract reskilled labor.

These thresholds are influenced by macroeconomic factors such as AI investment costs (C), public training subsidies (which reduce τ_i), and minimum wage laws (which affect w_i).

We can summarize the equilibrium outcomes in Table 1:

Table 1: Equilibrium outcomes

Occupation	σ (Substitution Elasticity)	Automation Risk	Equilibrium Outcome
High-skill	Low (0.2–0.4)	Low	Wage increase; labor inflow
Middle-skill	High (1.2–2.0)	High	Displacement; automation
Low-skill	Medium (0.5–0.7)	Medium	Expansion; wage stagnation

This framework provides a tractable yet flexible way to analyze how different occupations respond to AI adoption and how labor market polarization emerges endogenously from strategic interaction.

3. Simulation and Empirical Insights

This section provides simulation-based insights into the theoretical model developed in the previous chapter. Using stylized parameters and observed empirical trends, we explore how variation in occupational substitution elasticity and automation cost affects equilibrium labor outcomes. We also present two illustrative firm-level case studies—Shein and Amazon—to ground the model in real-world practices.

3.1. Simulation Design

To simulate the effects of AI adoption on labor market polarization, we define a simplified three-sector economy consisting of:

- High-skill labor (H): Engineers, data scientists, managerial professionals.
- Middle-skill labor (M): Clerical workers, manufacturing assemblers, technicians.
- Low-skill labor (L): Food service workers, janitors, personal care providers.

We fix the total labor supply at 100 units and simulate how labor redistributes in response to varying substitution elasticities (σ) and automation costs (C). Production is modeled using a CES function as introduced earlier, and AI capability A is an endogenous variable driven by firms' adoption decisions.

Table 2. Parameter Setup for Simulation

Parameter	Value	Description
σ_H	0.3	High-skill elasticity (low substitutability)
σ_M	[0.5, 2.0]	Middle-skill elasticity (varied in simulation)
σ_L	0.6	Low-skill elasticity (moderate substitutability)
C	[0.5, 2.0]	AI adoption cost index
w_H, w_M, w_L	Endogenously determined	Equilibrium wages

3.2. Results and Discussion

Simulation 1: Effect of σ_M on Employment Share

We fix C = 1.0 and vary σ_M from 0.5 to 2.0.

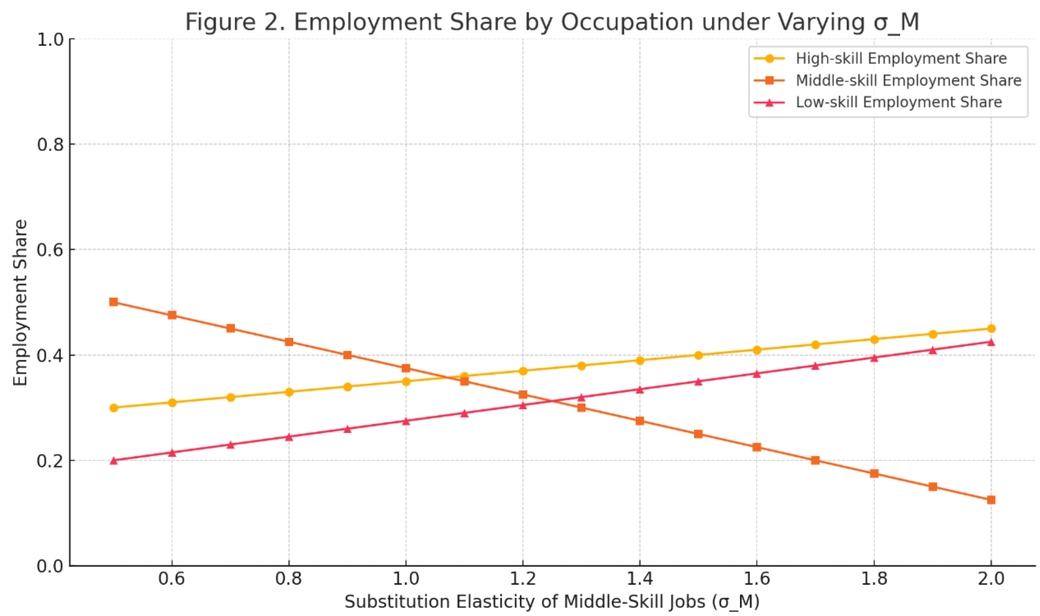

Figure 2. Employment Share by Occupation under Varying σ_M

As shown in Figure 2, increasing the substitution elasticity of middle-skill jobs leads to:

- A sharp decline in middle-skill employment.
- Migration to low-skill sectors, especially when retraining costs are high.
- A gradual increase in high-skill employment, assuming training infrastructure exists.

This pattern mirrors empirical trends observed in the U.S. and Europe, where jobs like bank tellers and clerical workers have seen net declines, while software and healthcare jobs have expanded.

Simulation 2: Interaction Between AI Cost and σ_M

We explore how automation risk depends on both σ_M and AI cost C.

Table 3. Automation Outcomes under Varying σ_M and AI Cost C

σ_M	C = 0.5 (Low)	C = 1.0 (Medium)	C = 2.0 (High)
0.5	Automation marginal	No automation	No automation
1.0	Moderate automation	Low automation	No automation
1.5	Extensive automation	Moderate automation	Marginal automation
2.0	Full replacement	Extensive automation	Moderate automation

This shows that both technological feasibility (σ) and economic viability (C) jointly determine automation outcomes. Policies that increase AI development costs—e.g., AI taxes—or lower retraining costs can shift equilibria toward more balanced employment structures.

3.3. Empirical Illustration: Case Study of Shein

Shein, a Chinese ultra-fast fashion platform, provides an illustrative case of how AI adoption can affect labor distribution. It utilizes:

- AI-driven demand prediction to determine fashion trends.
- A glocalized supply chain, relying on small-scale domestic producers with agile response cycles.

Labor impact:

- Middle-skill roles in pattern-making, order processing, and logistics are increasingly automated.
- Low-skill workers remain critical in packaging and flexible manufacturing.
- High-skill labor in data science and fashion forecasting is rapidly expanding.

Shein's model reflects the logic of the game-theoretic model: given high σ_M, the firm automates these tasks but retains low-skill tasks due to lower elasticity.

3.4. Empirical Illustration: Case Study of Amazon

Amazon provides a contrasting example with a heavy investment in robotics and fulfillment center AI.

- Warehouse picking robots and automated logistics scheduling have displaced large segments of middle-skill logistical staff.
- High-skill AI engineers are essential to algorithm design and maintenance.
- Low-skill workers continue to perform last-mile delivery and customer service.

Amazon's extensive use of AI for inventory management, predictive shipping, and customer profiling illustrates the capital-intensive strategy of large firms. Labor polarization is clearly visible in the reduction of mid-tier management and operational staff, and expansion of both top-tier engineers and bottom-tier logistics workers.

3.5. Policy Implications of Simulation

The simulation results suggest several policy takeaways:

1. Targeted retraining programs should focus on transitioning displaced middle-skill workers to low-barrier high-skill positions (e.g., tech support, data annotation).
2. AI taxation or adoption caps may reduce incentives to fully automate highly substitutable occupations.
3. Incentives for human-AI complementarity (e.g., co-bot design, hybrid systems) can reduce labor displacement.

These insights build on the model's formal logic to generate actionable guidance for policymakers and corporate strategists.

4. Model Analysis and Results

4.1. Equilibrium Conditions

- If σ_M is high, AI adoption becomes dominant for the firm.
- High-skill labor is retained, as its tasks are complementary to AI.
- Low-skill labor sees mixed effects—partial displacement or wage suppression.
- Middle-skill jobs are automated aggressively, reducing demand drastically.

4.2. Polarization Outcome

The model predicts that under high substitution elasticity for middle-skill labor:

- Wages for M fall, or jobs are eliminated.
- H wages rise, due to complementarities with AI.
- L employment becomes more prevalent, though under wage pressure. This mirrors real-world patterns of labor market polarization.

5. Discussion

The model provides a formal structure for understanding how technological adoption decisions are shaped not only by cost-benefit analyses, but also by task-level characteristics of labor. It supports the empirical claim that routine-intensive, middle-skill jobs are most at risk (Acemoglu & Restrepo, 2020), and adds strategic insight into firm behavior.

Implications:

- Education and training policy must focus on either high-skill upskilling or protecting low-skill service work.
- Wage subsidies or tax credits could incentivize firms to retain human workers in partially substitutable roles.
- Dynamic regulation of AI deployment based on sectoral elasticity could mitigate the

polarization trajectory.

6. Conclusion

This paper presents a novel game-theoretic framework to explain how AI adoption leads to labor market polarization. By incorporating occupational substitution elasticity, we show that firms strategically displace labor where replacement is easiest—middle-skill jobs—while retaining high-skill complements and low-skill manual labor. The theoretical findings align with global trends and offer actionable insights for managing the future of work in an AI-driven economy.

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