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Effects of New Technology Adoption in Korea: Implications for Growth, Employment, and Inequality

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Effects of New Technology Adoption in Korea: Implications for Growth, Employment, and Inequality

This paper studies how new technologies interact with labor-market frictions to shape aggregate and distributional outcomes in a Korean context. We build a quantitative heterogeneous-agent general equilibrium model with incomplete markets in which households choose between working fixed hours and investing time in learning, subject to convex human-capital adjustment costs. Firms combine capital and effective labor and face quadratic costs of adjusting employment. In the benchmark polarized scenario, long-run output, consumption, and investment all increase, but aggregate employment falls as workers reallocate time from market work toward human-capital accumulation. This reallocation generates endogenous job polarization across skill groups and raises income and consumption inequality. Labor-market frictions are crucial for the magnitude and persistence of these effects: slow, costly skill adjustment amplifies transitional employment losses and distributional gaps. Finally, we show that the sectoral direction of technological change—which skill group the technology favors—plays a central role in shaping both macroeconomic performance and inequality.

Keywords: Technological progress, Labor-market frictions, Human-capital accumulation, Job polarization

JEL Classification: E24, J24, O33, D52

I. Introduction

Rapid advances in artificial intelligence (AI) and related digital technologies are expected to transform the structure of labor demand and the distribution of income. A large empirical literature documents job polarization—the decline of middle-skill routine employment relative to low- and high-skill occupations—as automation diffuses through advanced economies (e.g., Acemoglu and Restrepo, 2020 among others).[1] At the same time, employment protection, limited use of flexible hours, and high retraining costs make it difficult for workers to respond quickly to changing task demands, especially in economies such as Korea.[2] These observations suggest that both the direction of technological change and labor-market frictions are central for understanding how new technologies affect macroeconomic outcomes, human-capital accumulation, and inequality.

This paper develops such a framework and applies it to the Korean economy. We build a quantitative heterogeneous-agent general equilibrium model with incomplete markets, endogenous human-capital accumulation, and three labor-market frictions: indivisible labor supplied on the extensive margin as in Chang and Kim (2006), convex human-capital adjustment costs on the household side (Naval, Silva and Vazquez-Grenno, 2020), and quadratic employment adjustment costs on the firm side (Dossche, Gazzani and Lewis, 2022). Households are ex-ante identical but become heterogeneous over time in financial assets, idiosyncratic productivity, and human capital. They choose whether to work a fixed amount of hours or not work at all, and they allocate time between market work and discrete learning efforts. Human capital accumulates gradually and is subject to depreciation and convex adjustment costs, so large skill upgrades are time-consuming and costly. A representative firm hires capital and human-capital–adjusted labor to produce output, but faces costs when changing its workforce, generating sluggish employment dynamics.

The model is disciplined using Korean data on employment, training incidence,

1) For discussions of job polarization, see Goos and Manning (2007), Autor and Dorn (2013), and Acemoglu and Restrepo (2020).
2) See Dossche, Gazzani and Lewis (2022) for discussion of employment adjustment and Naval, Silva and Vazquez- Grenno (2020) for human-capital adjustment costs.

and the joint distribution of income and wealth. Indivisible labor captures the predominance of full-time jobs and the limited margin of hour adjustment. Discrete, time-intensive learning choices reflect the reality that substantial retraining in Korea often requires leaving work temporarily to pursue credentials, formal programs, or intensive study. Employment adjustment costs on the firm side proxy for separation costs, seniority-based pay, and institutional rigidities that discourage rapid hiring and firing. Calibrated to match key moments—including the employment rate, the share of individuals engaged in human-capital investment, and the income Gini coefficient—the model generates a realistic steady state that mirrors salient features of the Korean labor market and cross-sectional distributions.

Within this framework, we study how different forms of technological progress affect aggregate outcomes, human-capital dynamics, and inequality. Technology is modeled as sector-specific productivity for three groups of tasks—low-, middle-, and high-skill—determined by workers' human-capital levels. Our benchmark experiment introduces a polarized technological shock, designed to capture automation or AI that complement elementary services and advanced cognitive tasks but substitute for routine middle jobs. The shock raises general productivity (e.g., TFP) while reducing productivity in the middle sector. We compute the deterministic transition from the initial steady state to the new equilibrium, tracking aggregates, sectoral employment, the distribution of human capital, and welfare.

In the benchmark experiment, this shock generates a rich but ultimately expansionary transition at the aggregate level. On impact, output, consumption, and investment all increase, reflecting the higher overall efficiency of production and firms' desire to accumulate capital in anticipation of more skill-intensive production.[3] The return on capital rises sharply at the time of the shock and then gradually declines toward a new, slightly higher steady-state level as the capital stock adjusts. Real wages also increase and remain persistently above their pre-shock levels, supported by both the aggregate TFP gain and endogenously accumulated capital. Employment behaves quite differently from other aggregates. It initially rises modestly but then declines along the transition and settles below its initial steady-state level. This fall

3) Most of these dynamics are consistent with the effects of news and anticipated technology shocks discussed by Barsky and Sims (2011).

in employment does not reflect a weaker economy; rather, it arises from a structural reallocation of time away from market work toward human-capital accumulation. As returns to high-skill tasks increase and middle-skill productivity deteriorates, more households choose to temporarily withdraw from employment and invest in skills, especially those close to the high-skill cutoff. The long-run equilibrium thus features higher output, consumption, capital, and wages, but lower aggregate employment. In this sense, polarized technological progress is growth-enhancing but employment-saving at the aggregate level.

The same polarized shock that boosts aggregate activity also generates pronounced and gradual distributional changes. First, the sectoral structure becomes more polarized. The population share and employment level in middle-skill jobs decline sharply and persistently, while both low- and high-skill groups expand. Displaced middle-skill workers either move into relatively well-paying low-skill jobs without investing further in human capital, or exit employment to retrain for high-skill positions; in both cases, the transition is slow because of human-capital adjustment costs. This endogenous hollowing-out of the middle propagates through earnings, consumption, and wealth. Income and earnings inequality initially move little but then rise persistently above their pre-shock levels. As the middle group shrinks and wage premia for high-skill tasks increase, the dispersion of labor income widens. Some households experience prolonged non-employment spells while accumulating human capital, while others remain locked in low-skill positions; both patterns depress earnings relative to high-skill workers who are able to exploit the new technology. Consumption inequality tracks income inequality with some smoothing: incomplete markets allow partial, but not full, insurance against earnings risk, so persistent differences in earnings capacity eventually translate into persistent differences in consumption.

Frictions in human-capital adjustment are the main reason why polarized technological change generates a deep and uneven transition. When skill adjustment is costly and slow, displaced middle-skill workers often need to leave jobs or postpone upgrading, so employment falls and aggregate reallocation is gradual. Removing these frictions changes the picture: workers can upgrade skills while staying employed, the employment decline largely disappears, and aggregate quantities rise more smoothly. Inequality still increases, but in a different way—there is an early

spike as high-ability, high-wealth households move quickly into top jobs, followed by a more stable path because long non-employment spells for retraining no longer occur. By contrast, removing frictions in firms' employment adjustment leaves the main macro and distributional results almost unchanged. Output, consumption, wages, and long-run inequality look very similar to the benchmark; only employment becomes more volatile and reacts faster to sectoral productivity changes. Thus, it is worker-side frictions in skill adjustment, rather than hiring and firing rigidities, that drive the depth of the downturn and the persistence of distributional effects in response to polarized technological progress.

We also show that the sectoral direction of technological change—which tasks the technology favors—critically shapes the trade-off between growth, skill upgrading, and inequality. We therefore consider two additional experiments that redistribute the same long-run productivity gain across sectors. In a low-skill-biased scenario, productivity gains are concentrated in low-skill tasks, while middle-skill productivity still falls and high-skill tasks do not receive extra benefits. This dampens the hollowing-out of the middle, raises low-skill earnings and employment, and keeps income and consumption inequality comparatively low. However, it weakens incentives for human-capital investment, reduces the aggregate human-capital stock, and ultimately yields smaller long-run gains in output, with higher dispersion in human capital and wealth. In a high-skill-biased scenario, by contrast, the productivity gains accrue only to high-skill tasks. This configuration delivers the strongest expansion in output, consumption, and total human capital and induces broad-based upgrading into the high-skill group, while keeping income and consumption inequality at or below the levels observed under polarized progress. Taken together, the three experiments trace out a clear frontier: low-skill bias is more inclusive but slows skill accumulation and growth, while high-skill bias promotes intensive upgrading and stronger growth with only a contained increase, if any, in inequality.

Related Literature The paper is related to several strands of literature. A first and most direct point of contact is the literature documenting job polarization. Goos and Manning (2007) show that since the mid-1970s the United Kingdom has witnessed a "hollowing out" of middle-wage occupations, with employment shares rising at the bottom and the top of the wage distribution. Autor and Dorn (2013) provide

a unified account of how computerization and routine-biased technological change depressed routine middle-skill jobs while expanding low-skill service employment in the United States. Goos, Manning and Salomons (2009) document similarly pervasive polarization across 16 advanced European economies. At a more micro level, Acemoglu and Restrepo (2020) show that industrial robots reduce both employment and wages in U.S. commuting zones exposed to robot adoption. The benchmark "polarized" technological shock in this paper is directly motivated by this evidence: productivity falls in middle-skill tasks while improving at the tails, and the model is used to trace the resulting transition in employment, human capital, and inequality in a Korean setting.

A second strand examines the broader labor-market consequences of robots and AI. Lerch (2021) argues that rising robot penetration not only displaces workers in affected industries but also contributes to lower overall labor-force participation. Faber, Sarto and Tabellini (2022) similarly show that automation reduces job opportunities in sectors with high robot intensity, with adverse consequences for both employment and earnings. These findings suggest that technological progress may lower aggregate employment even when it raises productivity, especially when workers face frictions in moving across occupations. The present paper echoes this insight: in the benchmark transition, aggregate output ultimately rises, but employment falls in the long run because workers devote more time to skill acquisition and because middle-skill jobs become structurally less valuable.

A growing body of work studies how workers adjust their educational choices and human-capital investment in response to automation risk. Atkin (2016) and Beaudry, Green and Sand (2016) argue that workers may self-insure against technological displacement by accumulating additional education rather than relying solely on rising skill premia. Di Giacomo and Lerch (2023) provide direct evidence from U.S. local labor markets that robot adoption stimulates college enrollment—especially in community colleges—with roughly four additional students enrolling for each additional robot. Dauth et al. (2021) show that German firms that adopt robots increase the share of college-educated workers in their employment mix, indicating a shift in demand toward more highly educated labor. The model in this paper is designed precisely to capture such behavioral responses: households can respond to a changing task structure by reallocating time between work and learn-

ing, subject to convex human-capital adjustment costs. Moreover, the anticipation of future technological change in the model relates to the literature on news and anticipated technology shocks, such as Barsky and Sims (2011), who emphasize how expectations about future productivity improvements can drive current macroeconomic fluctuations.

A fourth related literature emphasizes the implications of automation and AI for inequality, with a particular focus on education and wealth. Prettner and Strulik (2020) develop a growth model in which innovation raises the share of college-educated workers and, as a result, increases both income and wealth inequality over time. Sachs and Kotlikoff (2012), using an overlapping-generations framework, show how automation and skill-biased technical change can entrench inequality across cohorts by favoring highly educated workers and depressing wages for the less skilled. In both cases, technological progress tilts the distribution of income and wealth towards those with higher human capital. This paper is a direct extension of Lu and Ma (2025), who develop an incomplete-markets general equilibrium model with endogenous asset accumulation in which households choose human-capital investment and labor supply. They show that human-capital responses to AI amplify its positive effects on aggregate output and consumption, dampen the AI-induced rise in precautionary savings, and stabilize the adjustment of wages and asset returns. The present paper extends their quantitative framework by incorporating explicit labor-market frictions and calibrating them to the Korean context.

The paper is also connected to the literature on labor-market frictions in macro models. On the household side, Andolfatto (1996) introduces search frictions with both intensive and extensive labor margins in a representative-agent framework. Chang and Kim (2007) incorporate an extensive margin of labor supply into an incomplete-markets heterogeneous-agent model and show that this margin is important for business-cycle fluctuations. Rogerson and Wallenius (2009) examine an environment with both intensive and extensive margins, albeit without aggregate uncertainty, to study how indivisible labor affects the responsiveness of hours and employment. Nakajima (2012) embeds search and matching frictions into an incomplete-markets structure with both margins of labor adjustment, highlighting the role of unemployment risk for wealth accumulation and inequality. On the firm side, Dossche, Gazzani and Lewis (2022) estimate firm-level employment adjust-

ment costs and show that they are quantitatively important for employment dynamics. The current paper borrows from this literature by combining indivisible labor, forward-looking employment demand with adjustment costs, and incomplete markets, and uses this structure to study how labor-market frictions shape the transition to a new technological regime.

Finally, the paper relates to work on human-capital adjustment frictions. Lentz and Roys (2024) develop a model that combines on-the-job search with training decisions, emphasizing that workers face costs of changing their skill levels and that these costs interact with job mobility. Naval, Silva and Vazquez-Grenno (2020) model training costs on the firm side as a convex adjustment cost to human capital, analogous to standard investment adjustment costs for physical capital. These studies highlight that skill accumulation is gradual and costly, and that both workers and firms face frictions when upgrading human capital. The present model adopts a similar spirit: human-capital adjustment costs are convex and sizable, making rapid skill changes difficult and generating realistic, gradual learning paths. The paper shows that these frictions, more than firm-side employment adjustment costs, are the key bottleneck in reallocating labor in response to AI-type technologies.

Taken together, this paper contributes to and bridges the literature by embedding sector-specific technological change, human-capital choices, and rich labor-market frictions into a quantitative heterogeneous-agent framework calibrated to Korea. It complements empirical work on polarization and automation by providing a structural account of the transitional dynamics of output, employment, skills, and inequality, and it adds to the theoretical literature by comparing polarized, low-skill-biased, and high-skill-biased technological progress within a single model that features both worker- and firm-side frictions.

Road Map The remainder of the paper is organized as follows. Section 2 presents the model, describing household behavior, firm decisions, and the three labor-market frictions, and defines competitive equilibrium along the transition path. Section 3 discusses the calibration to Korean data and evaluates the model's fit to key aggregate and distributional moments. Section 4 analyzes the benchmark polarized technological progress experiment, documenting its implications for aggregate dynamics, job polarization, human-capital investment, inequality, and welfare, and

quantifying the roles of human-capital and employment adjustment costs. Section 5 compares the polarized case with low-skill-biased and high-skill-biased technological change, highlighting the trade-offs between growth, the pace of skill upgrading, and the composition of inequality. Section 6 concludes with implications for policy and directions for future research.

II. Model

1. Overview

This section presents a dynamic heterogeneous-agent general equilibrium model with incomplete markets, endogenous human-capital accumulation, and labor-market frictions. Time is discrete and indexed by $t = 0, 1, 2, \ldots$. Households face idiosyncratic productivity shocks that cannot be perfectly insured, and they make forward-looking decisions about consumption, savings, labor supply, and the accumulation of skills. A representative firm hires labor and capital to produce output but faces frictions that impede rapid adjustments in employment. The equilibrium dynamics arise from the interaction between household behavior, firm behavior, and the evolving distribution of individual states in the economy.

A key feature of the model is its structural flexibility. No specific technological environment is imposed at this stage; technology is kept entirely general so that later sections can introduce various forms of technological change—such as skill-biased, routine-biased, sector-specific, or human-capital-complementary innovations—without altering the fundamental behavioral structure. The model therefore provides a flexible foundation for studying long-run transitions in economies with heterogeneous households and endogenous skills.

The model incorporates three labor-market frictions that are particularly relevant in the Korean context. Employment in Korea tends to adjust mainly through movements into and out of jobs rather than through variations in hours, reflecting strong full-time employment norms and limited availability of flexible work arrangements. This motivates an extensive-margin, indivisible labor choice. Workers also face substantial costs when upgrading skills or switching occupations, as retraining typically requires significant time, credentials, or formal programs. These

human-capital adjustment frictions imply that skill accumulation is gradual and that differences in skills persist across individuals. On the firm side, employment responds sluggishly because hiring and firing are costly, partly due to training burdens, legal constraints, and organizational rigidities.

Taken together, these frictions create an environment where labor reallocation is slow, occupational mobility is limited, and skill differences persist over time. Embedding these features into the model allows it to capture salient characteristics of the Korean labor market and provides a realistic framework for analyzing shocks, policy interventions, and long-run structural change.

2. Households

Each household's circumstances at the start of period t are described by the triple

$$\Omega_t = (a_t, z_t, h_t),$$

representing financial wealth, idiosyncratic labor productivity, and human capital, respectively.[4] These states jointly determine the household's earnings potential, ability to accumulate future skills, and consumption-smoothing capacity. Because the markets are incomplete as in Huggett (1993) and Aiyagari (1994) and insurance against productivity shocks does not exist, these states evolve in ways that can differ substantially across households. This generates rich equilibrium heterogeneity.

2.1. Preferences

Preferences are separable in consumption, labor supply, and skill-acquisition effort. Each household derives instantaneous utility according to

$$u(c_t, n_t, s_t) = \log c_t - B_n n_t - B_s s_t,$$

4) In principle, learning ability would enter as an additional state variable, making the household state four-dimensional. However, to reduce the dimensionality of the problem, and because learning ability is assumed to be perfectly correlated with idiosyncratic productivity in line with the empirical evidence, we do not model it as a separate state variable.

where c_t denotes consumption, n_t denotes labor supply, and s_t denotes effort devoted to learning. The parameter B_n governs the cost of supplying labor, while B_s captures the cost of investing time in human-capital accumulation. These preferences reflect the idea that both work and learning require mental or physical effort that displace leisure or other activities.

Lifetime utility, U, is defined recursively as

$$U = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t u(c_t, n_t, s_t) \right],$$

where $0 < \beta < 1$ is subjective discount factor.

2.2. Idiosyncratic Productivity

Households are subject to persistent idiosyncratic productivity shocks that affect their potential earnings. Productivity evolves stochastically according to

$$\log z_{t+1} = \rho_z \log z_t + \varepsilon_{t+1}, \qquad \varepsilon_t \sim N(0, \sigma_z^2),$$

where ρ_z measures persistence, and σ_z measures the degree of heterogeneity. This specification implies that productivity shocks have long-lasting effects, giving rise to serially correlated earnings risk. Productivity follows a finite-state Markov chain, $z \in \{z_1, ..., z_{n_z}\}$, where $\Pr(z' = z_j | z = z_i) = \mathbf{Q}^{\mathbf{z}}(i, j) \geq 0$ and $\sum_{j=1}^{n_z} \mathbf{Q}^{\mathbf{z}}(i, j) = 1$ for all i. Because there is no market for state-contingent insurance in the model, households must rely on savings and human-capital investment as imperfect means of self-insurance, generating precautionary behavior and heterogeneous wealth accumulation.

2.3. Indivisible Labor Supply

Labor supply is discrete. A household may supply a fixed amount $\bar{n}$ of labor or none at all:

$$n_t \in \{0, \bar{n}\}.$$

This representation follows the classic indivisible-labor formulation of Hansen (1985) and Rogerson (1988), which views employment as primarily an extensive-margin choice.[5] This structure is particularly useful here because the decision to work or not directly shapes the household's ability to invest in human capital. A household that chooses $n_t = 0$ enjoys additional time that can be allocated to learning, potentially accelerating future skill acquisition. Later in the model, we explicitly assume that employment status restricts the amount of time that can be allocated to skill investment, making the extensive-margin work decision a key determinant of human-capital dynamics.

2.4. Human-Capital Accumulation

Households accumulate human capital over time, and this evolving skill level plays a central role in shaping their future earnings potential and occupational opportunities. Human capital evolves according to

$$h_{t+1} = x_t s_t + (1 - \delta_h) h_t - AC_h(h_{t+1}, h_t),$$

where x_t is learning ability,[6] s_t denotes time devoted to training, and δ_h is the depreciation rate. This formulation incorporates two key features of human-capital dynamics. First, human capital increases with active investment: individuals who allocate more time to learning or training can expand their skill set. Second, human capital naturally depreciates if not maintained, reflecting the erosion of knowledge and abilities when they are not regularly used or updated. A crucial component of the specification is the presence of human-capital adjustment costs,

$$AC_h(h_{t+1}, h_t) = \frac{\Theta_h}{2}(h_{t+1} - h_t)^2,$$

where Θ_h governs the magnitude of these costs. The adjustment cost makes large, rapid changes in skill levels expensive, thereby generating gradual learning paths

5) Chang and Kim (2006) and Chang and Kim (2007) introduced indivisible labor in incomplete-markets environments.
6) We later assume that learning ability is assumed to be perfectly correlated with idiosyncratic productivity.

and preventing unrealistic jumps in human capital from one period to the next. This captures the idea that meaningful skill upgrading requires sustained effort, time, and resources—not instantaneous adjustments—and helps produce realistic heterogeneity in workers' learning and career trajectories. The convex cost ensures that households accumulate skills gradually. It reflects the time, resources, cognitive constraints, and institutional barriers involved in acquiring human capital.

In combination with indivisible labor, this framework generates meaningful heterogeneity in learning trajectories. Because working and learning compete for time, some households optimally choose periods of full-time training—setting $n_t = 0$ and investing intensively with $s_t = s_H$ —in order to accelerate their transition into higher-skill occupations. Others remain employed and engage only in modest on-the-job learning, selecting the lower effort level s_L when $n_t = \bar{n}$. Skill investment effort is discrete,

$$s_t \in \{0, s_L, s_H\},$$

with $s_H > s_L$, and the choice set is restricted by employment status:

$$s_t \in \begin{cases} \{0, s_L, s_H\}, & n_t = 0, \\ \{0, s_L\}, & n_t = \bar{n}. \end{cases}$$

This structure reflects the idea that intensive skill upgrading typically requires dedicated time away from work, as substantial occupational changes or major skill transitions often demand stepping out of employment to engage in formal retraining or concentrated study. As a result, households differ systematically in how and when they accumulate human capital, giving rise to gradual and heterogeneous learning paths across the population.

2.5. Earnings and Sectoral Productivity

Effective labor productivity depends not only on the idiosyncratic productivity shock z_t but also on the level of human capital. To capture broad occupational differences in a parsimonious way, we partition human capital into three segments and

map them into sector-specific productivities:

$$q(h_t) = \begin{cases} 1-\omega, & h_t < h_M, \\ 1, & h_M \le h_t < h_H, \\ 1+\omega, & h_t \ge h_H. \end{cases}$$

The thresholds h_M and h_H classify individuals into low-, middle-, and high-skill groups, respectively. The parameter ω governs the skill premium: it controls how much more (or less) effective high-skill and low-skill labor are relative to middle-skill labor. This formulation allows human capital to determine not only a worker's wage but also the type of task they supply to the production sector. Low-skill workers contribute less effective labor, middle-skill workers supply tasks of baseline productivity, and high-skill workers supply tasks that are more productive by a factor proportional to ω. Given this structure, labor income is

$$y_t = n_t w_t z_t q(h_t),$$

where w_t is the wage per unit of effective labor. Thus, earnings vary across individuals due to differences in employment status, idiosyncratic productivity, and—critically—human-capital type. This mapping creates a direct link between human-capital accumulation decisions and long-run labor-market outcomes, making workers' learning choices central to their future earnings trajectories.

2.6. Budget Constraint

Given the interest rate r_t and wage w_t, the household's budget constraint is

$$c_t + a_{t+1} = y_t + (1+r_t)a_t, \qquad a_{t+1} \ge 0.$$

Households cannot borrow and have no access to state-contingent insurance markets. As a result, they must rely on their own savings and human-capital investment decisions to buffer idiosyncratic productivity risk and smooth consumption over time. This borrowing constraint amplifies the role of precautionary savings and creates meaningful heterogeneity in wealth accumulation across households.

2.7. Household Problem

The household's dynamic optimization problem can be written in recursive form as

$$V(a,z,h) = \max_{c,a',n,s,h'} \left\{ \log c - B_n n - B_s s + \beta \mathbb{E}_{z'} \left[V(a',z',h') \right] \right\}, \tag{1}$$

subject to the following constraints:

(1) Budget Constraint

$$c + a' = y + (1+r)a, \qquad a' \geq 0, \tag{2}$$

$$y = nwzq(h), \tag{3}$$

where $q(h)$ denotes sector-specific human-capital productivity, and the borrowing constraint $a' \geq 0$ reflects the absence of credit and state-contingent insurance markets.

(2) Human-Capital Accumulation

$$h' = xs + (1-\delta_h)h - AC_h(h',h), \tag{4}$$

$$AC_h(h',h) = \frac{\Theta_h}{2}(h'-h)^2. \tag{5}$$

(3) Feasible Skill-Investment Choices

$$s \in \begin{cases} \{0, s_L, s_H\}, & n = 0, \\ \{0, s_L\}, & n = \bar{n}, \end{cases} \qquad \text{with} \quad s_H > s_L \geq 0. \tag{6}$$

(4) Indivisible Labor Supply

$$n \in \{0, \bar{n}\}. \tag{7}$$

The household therefore chooses consumption c, next-period assets a', labor supply n, skill-investment effort s, and next-period human capital h' to maximize

its lifetime utility. The resulting policy functions,

$$c(a,z,h), \quad a'(a,z,h), \quad n(a,z,h), \quad s(a,z,h), \quad h'(a,z,h),$$

characterize the transition of individual states (a,z,h) over time. Aggregating these individual transitions yields the endogenous cross-sectional distribution of wealth, human capital, and earnings in equilibrium.

3. Firms

The production side consists of a representative competitive firm that combines capital K_t and effective labor L_t using a Cobb–Douglas technology,

$$Y_t = A_t K_t^{1-\alpha} L_t^{\alpha}, \tag{8}$$

where A_t denotes total factor productivity. Effective labor aggregates worker's human-capital-adjusted productivities,

$$L_t = \int n_t z_t q(h_t)\, d\mu_t. \tag{9}$$

A key labor-market friction in the model is that employment adjusts sluggishly. Following Dossche, Gazzani and Lewis (2022), the firm chooses employment E_t but faces a quadratic adjustment cost,

$$AC_E(E_t, E_{t-1}) = \frac{\Theta_E}{2}(E_t - E_{t-1})^2, \tag{10}$$

where Θ_E governs the magnitude of these costs. This term captures several empirically relevant features of the Korean labor market, including high costs of separation, seniority-based pay systems, extensive firm-specific training, and institutional rigidities that make rapid hiring or firing costly. As a result, firms in Korea tend to smooth employment over time rather than adjust instantaneously to shocks, making employment adjustment costs an important friction to include.

Taking wages w_t and interest rates r_t as given, the representative firm solves

$$\max_{\{K_t,L_t,E_t\}} \sum_{t=0}^{\infty} \beta^t \left[A_t K_t^{1-\alpha} L_t^{\alpha} - w_t L_t - r_t K_t - \frac{\Theta_E}{2}(E_t - E_{t-1})^2 \right]. \tag{11}$$

The optimality condition for capital satisfies

$$(1-\alpha) A_t \left(\frac{L_t}{K_t} \right)^{\alpha} = r_t, \tag{12}$$

while the labor condition incorporates the adjustment-cost term:

$$\alpha A_t \left(\frac{L_t}{K_t} \right)^{\alpha-1} - \Theta_E E_t \left[(E_t - E_{t-1}) + \beta (E_t - E_{t+1}) \right] = w_t. \tag{13}$$

The presence of the adjustment-cost term implies forward-looking labor demand: firms internalize both current and future deviations in employment, producing sluggish employment dynamics. These frictions interact with households' labor-supply and human-capital decisions and play a central role in shaping the transition dynamics analyzed in the subsequent sections.

4. Equilibrium Along the Transition Path

Let the individual state be (a,z,h) and let μ_t denote the cross-sectional distribution of households over these states at date t. Given an initial distribution μ_0 and a deterministic sequence of technology $\{A_t\}_{t=0}^{\infty}$ (and sector-specific productivities implicit in $q(\cdot)$), a *competitive equilibrium along the transition path* is a collection of sequences

$$\left\{ V_t(a,z,h),\, c_t(a,z,h), a_{t+1}(a,z,h), n_t(a,z,h), s_t(a,z,h), h_{t+1}(a,z,h);\, w_t, r_t;\, K_t, L_t, E_t;\, \mu_t \right\}_{t=0}^{\infty}$$

such that:

1. **Household optimization.** Given the entire sequences of prices $\{w_t, r_t\}_{t=0}^{\infty}$ and the law of motion for idiosyncratic productivity $\{z_t\}$, households take these objects as given and solve the dynamic programming problem described above. At each date t and for every individual state (a,z,h), they choose current con-

sumption, next-period assets, employment status, skill-investment effort, and next-period human capital to maximize expected lifetime utility, subject to the period budget constraint, the human-capital accumulation equation, the indivisible-labor choice, and the restrictions on learning effort. The solution yields, for each t, a value function $V_t(a,z,h)$ and associated policy functions

$$c_t(a,z,h), \quad a_{t+1}(a,z,h), \quad n_t(a,z,h), \quad s_t(a,z,h), \quad h_{t+1}(a,z,h).$$

2. **Firm optimization.** Given sequences of wages and interest rates $\{w_t, r_t\}_{t=0}^{\infty}$ and technology $\{A_t\}_{t=0}^{\infty}$, the representative firm chooses sequences $\{K_t, L_t, E_t\}_{t=0}^{\infty}$ to maximize the discounted sum of profits,

$$\sum_{t=0}^{\infty} \beta^t \left[A_t K_t^{1-\alpha} L_t^{\alpha} - w_t L_t - (r_t + \delta) K_t - \frac{\Theta_E}{2} (E_t - E_{t-1})^2 \right],$$

taking E_{t-1} as given.

3. **Factor markets clearing.** At each date t, aggregate capital, effective labor, and employment equal the aggregates of individual choices:

$$K_t = \int a \, d\mu_t(a,z,h),$$
$$L_t = \int n_t(a,z,h) \, z \, q(h) \, d\mu_t(a,z,h),$$

4. **Goods market clearing.** For each t, output is allocated to consumption, gross investment, and employment adjustment costs:

$$\int c_t(a,z,h) \, d\mu_t(a,z,h) + K_{t+1} - (1-\delta) K_t + \frac{\Theta_E}{2} (E_t - E_{t-1})^2 \; = \; A_t K_t^{1-\alpha} L_t^{\alpha}.$$

5. **Law of motion for the distribution.** The sequence $\{\mu_t\}_{t=0}^{\infty}$ is consistent with individual behavior and the exogenous productivity process. Given μ_t and the policy functions at date t, the next-period distribution μ_{t+1} is obtained by pushing forward μ_t through the optimal transition of (a,z,h) implied by $a_{t+1}(a,z,h)$, $h_{t+1}(a,z,h)$ and the transition matrix of z.

5. Discussion of the Three Labor-Market Frictions

A defining feature of the model is the presence of three labor-market frictions that operate at different margins and shape both individual decision-making and aggregate dynamics. Although each friction has a distinct origin and mechanism, they interact in meaningful ways and jointly determine how the economy responds to shocks, how households adjust their skills, and how employment evolves over time. Understanding the role of these frictions is essential for interpreting the model's predictions about labor supply, human-capital dynamics, and inequality.

5.1. Indivisible labor and the extensive margin

The first friction concerns the way households supply labor. In the model, households do not choose the number of hours continuously; instead, they face a binary decision: work a fixed amount or not work at all. This "indivisible labor" assumption captures a key empirical regularity: for most workers, labor-supply adjustments occur mainly on the extensive margin—entering or leaving employment—rather than through continuous changes in hours. Institutional features such as full-time work norms, fixed-hour employment contracts, and adjustment costs related to part-time employment reinforce this pattern.

This friction has two important implications. First, it amplifies idiosyncratic shocks. Because the household cannot finely adjust hours, even a small decline in productivity or human capital may push it from working to not working, causing a discrete drop in earnings. Second, indivisible labor interacts strongly with human-capital investment. When not working, a household has more time available for learning. Intensive skill investment, in particular, is only feasible during non-employment spells. This means that the choice to exit the labor market is not simply a response to low current productivity but can also be an investment decision aimed at improving future earnings. The friction therefore creates a realistic link between job mobility, periods of non-employment, and long-run skill acquisition.

5.2. Human-capital adjustment costs and micro-level skill frictions

The second friction arises from the difficulty of adjusting human capital. In the model, increasing human capital is expensive in a convex way: rapidly changing one's skill level incurs disproportionately large costs. This friction reflects the real-world barriers individuals face when attempting to move between occupations or acquire new capabilities. Skill acquisition demands time, effort, and sometimes financial resources. Furthermore, the learning process is rarely instantaneous; mastery of new tasks or professions often requires sustained and repeated practice. These features are captured in the model through an adjustment cost that makes skill accumulation gradual and prevents abrupt changes between skill categories.

This friction is especially important for understanding the distributional dynamics of the model. Because skill adjustment is costly, individuals differ persistently in their skill levels, even if their incentives to improve are similar. Some households will choose to invest in skills slowly due to high adjustment costs, even when higher human capital would yield a substantial return. As a result, the human-capital distribution responds sluggishly to economic shocks, including those that later may represent technological change. The adjustment cost also interacts with the indivisible labor margin: since intensive investment is only possible when not working, the model naturally produces a pattern where skill upgrading often happens during employment gaps. In this way, micro-level frictions in skill adjustment help generate realistic heterogeneity in earnings mobility, occupational transitions, and wage persistence.

5.3. Employment adjustment costs and firm-level labor frictions

The third friction operates on the firm side. Even though firms behave competitively, they do not adjust employment freely; instead, they face costs when changing the size of their workforce. These might reflect the cost of hiring and firing workers, legal restrictions on layoffs, time required to train new employees, or organizational costs associated with reorganizing labor across tasks. In reality, firms tend to smooth employment over time, adjusting only gradually to changes in demand or productivity. The model captures this behavior through a quadratic adjustment cost that penalizes deviations in employment from one period to the next.

This firm-level friction introduces inertia in aggregate labor demand. Wages do not instantly track productivity shocks, nor does employment respond mechanically to current conditions. Instead, firms partially absorb shocks through gradual employment adjustments. This slow adjustment interacts with household behavior: with employment levels sluggish, households may face temporarily limited opportunities to work even if their productivity rises. Conversely, even in periods of expansion, firms may not fully increase employment if doing so incurs excessive adjustment costs. This stickiness in employment contributes to time-varying wages, fluctuating job-finding probabilities, and sectoral differences in employment dynamics.

5.4. Interactions among the three frictions

Although each friction plays a distinct role, their interaction is crucial for producing the model's rich dynamics. The indivisible labor decision creates a strong connection between employment and skill investment. Human-capital adjustment costs create persistence in occupational status and slow transitions across skill categories. Employment adjustment costs on the firm side generate fluctuations in labor demand that influence households' ability to work and, indirectly, their incentives to invest in skills.

Together, these frictions create an environment in which both micro-level and macro-level factors shape long-run skill outcomes, employment patterns, and inequality. The model does not generate immediate reallocation of labor in response to shocks; instead, changes propagate slowly as firms adjust employment and as workers gradually accumulate new skills. This structure is essential for studying long-run transitions, such as those associated with new technologies, evolving task demands, or shifts in sectoral productivity.

III. Calibration

1. Parameterization

We calibrate the model to match the Korean economy. For several preference parameters, we adopt values commonly used in the literature. Other parameters are

Table 1. Parameters for the Calibration

Parameter	Value	Description	Target or Reference
β	0.9407	Time discount factor	Annual interest rate
ρ_z	0.80	Persistence of z shocks	KLIPS
σ_z	0.23	Standard deviation of z shocks	KLIPS
ω	0.2	Skill premium	Income Gini
B_n	2.91	Disutility from working	Employment rate
B_s	1.46	Disutility from HC effort	See text
$\bar{n}$	1/3	Hours worked	Average hours worked
s_H	1/3	High level of effort	Average hours worked
s_L	1/6	Low level of effort	See text
h_M	0.82	HC cutoff for M	See text
h_H	1.40	HC cutoff for H	See text
α	0.36	Capital income share	Standard value
δ	0.06	Capital depreciation rate	Standard value
δ_h	0.1	HC depreciation rate	See text
Θ_h	0.5	HC adjustment cost	See text
Θ_E	0.5	Employment adjustment cost	See text

calibrated to align with targeted moments. The model operates on an annual time period. Table 1 summarizes the parameter values used in the benchmark model.

Time Preference The time discount factor, β, is calibrated to match an annual interest rate of 4 percent.

Labor Productivity Process and Skill Premium We calibrate parameters regarding labor productivity process as follows. We assume that z follows the AR(1) process in logs:

$$\ln z_{t+1} = \rho_z \ln z_t + \sigma_z \varepsilon_{t+1}, \qquad \varepsilon_{t+1} \sim \mathcal{N}(0,1),$$

where (ρ_z, σ_z) are taken directly from existing empirical estimates in the literature on income and earnings dynamics. The shock process is discretized using the Tauchen (1986) method, resulting in a transition probability matrix with 9 grids. The persistence parameter $\rho_z = 0.8$ and the standard deviation $\sigma_z = 0.23$, which are from the literature based on Korean Labor & Income Panel Study (KLIPS). To reduce the dimensionality of the problem, we assume that learning ability, x_t, is perfectly correlated with labor productivity, z_t, which is in line with the empirical evidence.

The parameter governing the relative productivity of high-skilled workers, denoted ω, is calibrated to match the empirical Gini coefficient of income in the initial steady state.

Time Allocated to Skill Accumulation Households differ in the time that must be devoted to human-capital acquisition. We set

$$s_L = 20 \text{ hours/week}, \qquad s_H = 40 \text{ hours/week},$$

corresponding to low and full investment, respectively. Full-time human-capital investment is modeled as equivalent to a standard full-time workweek of 40 hours, while low investment requires only half that amount of time (20 hours per week).

Human-Capital Cutoffs The thresholds that determine skill types are calibrated to match the empirical distribution of workers across the low-, middle-, and high-skill categories. Let h_M denote the cutoff for middle-skill workers transitioning into high-skill status, and h_H denote the cutoff for high-skill classification. The calibration chooses (h_M, h_H) such that the steady-state population shares satisfy a 30–40–30 split across low-, middle-, and high-skill groups:

$$\Pr(h < h_M) = 0.30, \quad \Pr(h_M \le h < h_H) = 0.40, \quad \Pr(h \ge h_H) = 0.30.$$

Disutility of Labor and Learning Preferences feature separate disutility parameters for labor supply and human-capital investment. The calibration jointly targets (i) the aggregate employment rate and (ii) the human-capital investment rate of 33% observed in micro survey data.[7] In steady state, these parameters ensure realistic participation margins and training intensity:

$$\Pr(n > 0) \approx 0.70, \qquad \Pr(s > 0) \approx 0.33.$$

Other Parameters We assume $\bar{n} = 1/3$, meaning workers allocate 40 hour per week to labor. On the production side, we set the capital income share, α, to 0.36,

7) Refer to Bank of Korea Issue Notes 2025-22.

Table 2. Key Moments

Moment	Data	Model
Employment rate	0.70	0.70
New Investment Pop. ratio	0.33	0.34
Gini coefficient for wealth	0.62	0.63
Gini coefficient for income	0.41	0.41

and the depreciation rate, δ, to 0.06, standard in the Korean macroeconomic calibration literature. We assume that the depreciation rate of human capital is 10%, $\delta_h = 0.1$. In addition, we set

$$\Theta_h = 0.5, \qquad \Theta_E = 0.5,$$

which govern the costs of human-capital adjustment and employment adjustment, respectively. Because these parameters are only weakly disciplined by the data, we treat them primarily as objects for qualitative analysis.[8)]

Overall, the calibration aligns the steady-state properties of the model with key features of the Korean labor market and income distribution, thereby providing a disciplined baseline for the transition analysis that follows.

2. Model Fits

Table 2 evaluates whether the model replicates central aggregate indicators of the Korean economy, including the employment rate, the human-capital investment ratio, and measures of income and wealth inequality. The comparison between data and model outcomes is summarized as follows: The model exactly matches the aggregate employment rate of 70 percent. This is a targeted moment, but achieving it requires concordance between multiple parameters governing the labor-supply margin, idiosyncratic productivity risk, and firm adjustment frictions. A good fit here is essential because the employment level directly influences the distribution of earnings, the aggregate production level, and the opportunities for workers to invest in human capital. The model also reproduces the empirical share of time that house-

8) In particular, we later compare versions of the model with and without these frictions to assess how sensitive the transition dynamics are to the strength of these adjustment costs.

Table 3. Wealth and Income Shares by Quintile

	Quintile					Gini
	1st	2nd	3rd	4th	5th	
			Wealth Distribution			
Data	0.81	5.31	10.75	19.17	63.91	0.62
Model	0.08	2.49	9.51	25.41	62.49	0.63
			Income Distribution			
Data	1.25	8.91	17.01	26.31	46.72	0.41
Model	2.58	9.87	17.34	26.57	43.62	0.41

Note: This table reports the shares of net wealth and market income held by each quintile of the distribution in the data and in the benchmark model. Data moments are based on the 2019 KIPF Fiscal Panel.

holds allocate to human-capital investment. This is a particularly stringent moment because the model restricts intensive investment—represented by the high effort level —to periods of non-employment. Matching a 33 percent investment ratio indicates that the interaction of labor supply and learning frictions coherently captures the Korean institutional environment, where retraining periods, career breaks, and credential-based occupational transitions are common. The model closely reproduces the empirical Gini coefficients for wealth (0.63 vs. 0.62 in the data) and income (0.41 in both data and model). The former is not directly targeted but is an emergent property of the equilibrium distribution.[9] The close match indicates that the interaction of idiosyncratic risk, incomplete markets, and human-capital dynamics generates the appropriate degree of heterogeneity observed in the data.

A more demanding evaluation concerns the ability of the model to match the shape of the wealth and income distributions across quintiles. The empirical distribution from the 2019 KIPF Fiscal Panel exhibits substantial concentration of wealth and a moderate concentration of income. The model succeeds in reproducing these distributional patterns. The empirical wealth distribution is highly skewed, with the top quintile holding more than 63 percent of total wealth and the bottom quintile less than 1 percent. The model reproduces this degree of concentration remarkably well.

9) The wealth distribution is shaped primarily by precautionary savings and heterogeneity in earning ability, while income inequality reflects differences in wages across skill types, employment transitions, and the returns to human capital.

The bottom two quintiles remain wealth-poor due to limited precautionary savings and low earnings volatility, while the top quintile accumulates disproportionately large assets due to persistent productivity differences and high returns to human capital. The model also replicates the shape of the income distribution closely. The bottom quintile share is slightly higher in the model (2.6 percent vs. 1.3 percent in the data), reflecting the strong minimum productivity floor from the idiosyncratic shock process. However, the remaining quintiles match the data almost exactly, including the pivotal middle quintiles that are sensitive to employment dynamics and skill heterogeneity.

IV. Baseline Results: Polarized Technological Progress

This section examines the quantitative implications of polarized technological progress within the framework of the heterogeneous-agent economy described above. The model is solved along a deterministic transition path following the introduction of a structural technological shift that raises aggregate productivity while disproportionately benefiting low- and high-skill tasks and reducing productivity in middle-skill occupations. This shock generates a "hollowing-out" pattern consistent with job polarization: the relative efficiency of intermediate tasks declines gradually over time, while the productivity of low- and high-skill activities increases. The transition path is derived as a sequence of competitive equilibria and is evaluated at an annual frequency.

We organize the results around several key outcomes: aggregate quantities, labor-market reallocation, human-capital dynamics, earnings and wealth inequality, and the role of the three labor-market frictions. Throughout, we contrast the equilibrium transition under polarized technological progress with a counterfactual scenario in which the technological shock raises overall TFP but does not generate any polarization across occupations. This comparison allows us to isolate the contribution of polarization to aggregate and distributional dynamics.

1. Assumptions for Transitional Dynamics

To analyze the economic impact of polarized technological progress, we study the transition from the current steady state to a new steady state in which this tech-

nology is in place. The arrival of the new technology is fully anticipated: agents know that it will be implemented in ten years and form expectations accordingly.[10)]

First, polarized technological progress is assumed to hurt middle-skill. It primarily affects tasks performed in the middle sector, in line with the empirical literature on routine-biased technical change, which finds that automation disproportionately targets routine tasks typically carried out by middle-skilled workers (Goos, Manning and Salomons, 2009 among others). In the model, this is captured in two ways. On the productivity side, sector-specific efficiency in the middle sector is permanently reduced relative to the other groups: the effective productivity of middle-sector workers is scaled down by a factor $1-\lambda$ with $\lambda = 0.05$, while the productivity of low- and high-skill workers is unchanged apart from the aggregate TFP effect. On the quantity side, the new technology replaces 10 percent of middle-sector labor, generating a sector-specific decline in labor demand and earnings for middle-skill workers. These changes strengthen incentives for human-capital accumulation and reallocation toward the high-skill sector, and they naturally give rise to job polarization.

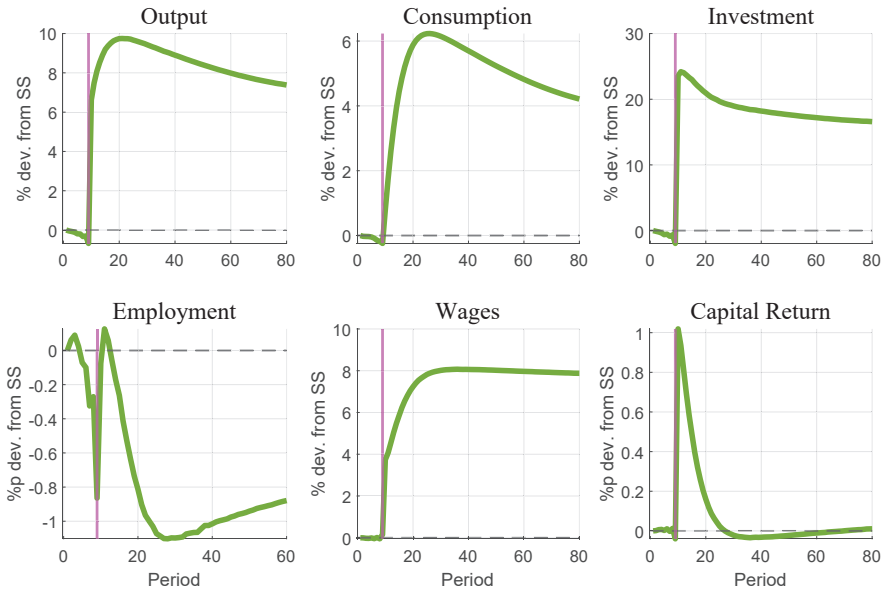
Second, we allow for a positive aggregate productivity effect of polarized technological progress. TFP increases by 5 percent, from $A = 1$ to $A = 1.05$. This captures the idea that, beyond its distributional and displacement effects, the new technology raises overall production efficiency and contributes to aggregate output growth, consistent with the broader literature on technology-driven improvements in TFP (e.g., Acemoglu and Restrepo, 2019).[11)]

Given these assumptions, the model solves for the full transition dynamics from the initial pre-technology steady state to the post-technology steady state, taking into account forward-looking behavior, changes in labor demand across skill groups, and

10) While one could alternatively consider a gradual introduction of the new technology—which may better reflect real-world adoption patterns—we adopt this framework to more clearly and sharply identify its effects. Modeling a discrete and fully anticipated implementation allows us to isolate the underlying mechanisms and transitional dynamics without conflating them with gradual diffusion or adjustment processes.

11) In our framework, new technology does not directly augment capital or effective labor; instead, it enters as TFP. However, through endogenous human capital adjustment, technological progress indirectly affects both capital and labor dynamics. A CES (Constant Elasticity of Substitution) specification allowing factor-specific complementarity could be considered, but this lies beyond the scope of our analysis.

Figure 1. Aggregate Responses to Polarized Technological Progress



Note: The figure plots percentage deviations of output, consumption, investment, employment, real wages, and the return on capital from their pre-technology steady-state levels. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

endogenous human-capital investment decisions.

2. Aggregate Effects

This subsection examines the aggregate dynamics triggered by the introduction of polarized technological progress. The shock raises productivity at the bottom and top of the skill distribution while reducing the relative efficiency of middle-skill tasks. The economy transitions gradually toward a new steady state as households adjust their labor supply, retraining decisions, and savings behavior, while firms reallocate labor across tasks subject to employment adjustment costs. Figure 1 summarizes the responses of output, consumption, investment, employment, wages, and capital returns along the transition.

Before technology adoption (anticipation phase). In the periods leading up to implementation, movements in macroeconomic aggregates are modest. Because the arrival date and nature of the technology are known in advance, households

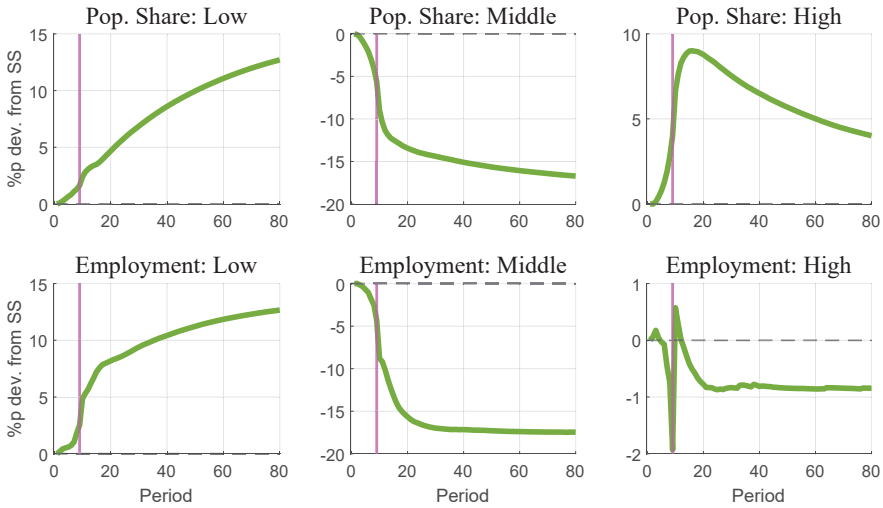
and firms begin to adjust gradually. Investment starts to edge up as firms anticipate higher future productivity and begin building the capital stock required for more skill-intensive production. Consumption responds more sluggishly, reflecting households' desire to smooth consumption over time. Employment remains close to its initial level in this phase, while wages and the return on capital show only limited pre-emptive movements.

On impact of polarized technological progress. When the new technology is implemented, the economy experiences a sharp expansion rather than a contraction. Output, consumption, and investment all jump on impact, with investment responding most strongly as firms accelerate capital accumulation to take advantage of higher productivity. Real wages increase steeply, reflecting both the aggregate productivity improvement and high capital. The return on capital spikes on impact because the technology shock raises the marginal product of capital relative to the pre-existing capital stock. Employment displays a short-run overshooting pattern: it initially rises as firms expand production in response to the favorable technology shock, but then begins to decline as households gradually reallocate time from market work to human-capital accumulation.

Long-run adjustment and new steady state. Over the longer horizon, the economy converges to a new steady state with higher output and consumption than in the pre-technology equilibrium. Investment remains persistently above its initial level, reflecting continued capital deepening in response to higher long-run productivity. Wages stay elevated throughout the transition, sustained by both the higher aggregate productivity and the increased capital stock. By contrast, employment settles below its original steady-state level. This decline does not signal weaker economic activity; instead, it reflects a structural reallocation toward more skill-intensive production, with households devoting more time to human-capital investment and less to market work, especially among workers who previously occupied middle-skill positions. Finally, the return on capital declines from its initial spike and gradually approaches a new level slightly above its pre-technology value due to the decreased labor.

Taken together, the figure illustrates how polarized technological progress gen-

Figure 2. Sectoral Employment and Job Polarization



Note: The top row shows the evolution of population shares in the low-, middle-, and high-skill groups relative to the initial steady state. The bottom row reports employment deviations by skill group. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

erates rich, non-monotonic transition dynamics: a strong expansion on impact, followed by gradual reallocation of labor and capital, and convergence to a more productive, more skill-intensive long-run equilibrium with higher wages and output but lower aggregate employment. Most of these dynamics mirror the responses to news and anticipated technology shocks documented by Barsky and Sims (2011).

3. Sectoral Effects and Job Polarization

This subsection examines how polarized technological progress reshapes the occupational structure of the economy. The shock increases productivity in low- and high-skill tasks while reducing productivity in middle-skill activities. As a result, households gradually reallocate across sectors through endogenous human-capital accumulation, and firms adjust their labor demand in response to changes in relative productivity. Figure 2 presents the transition dynamics of sectoral population shares and employment levels across the low-, middle-, and high-skill sectors.

A central result of the model is that job polarization arises endogenously, even though we impose exogenous heterogeneity in ex-post productivity across sectors.

In particular, a nontrivial part of polarization is generated by households' endogenous decisions about employment and human-capital accumulation. The top row of Figure 2 shows the evolution of the population shares in each skill group relative to the initial steady state. The share of workers in the low-skill sector rises steadily over time. As polarized technological progress erodes the relative productivity and earnings of middle-skill jobs, the effective premium between low- and middle-skill positions narrows, making low-skill employment relatively more attractive than remaining in a shrinking middle sector. In other words, rather than undertaking costly human-capital investment to move up, many middle-sector workers forgo retraining and shift into the low-skill sector. Hence, the middle-skill sector contracts sharply and persistently. The high-skill share increases for the opposite reason: the long-run return to advanced skills rises, and some middle-skill workers with sufficient ability and wealth choose to invest in additional human capital and gradually move up into the high-skill group. These shifts are slow because human-capital adjustment costs prevent immediate movement across categories. The eventual outcome is a hollowing-out of the middle of the distribution—middle-skill employment shrinks, while both low- and high-skill segments expand—which is the hallmark of polarization.

The bottom row of Figure 2 reports employment deviations in each sector. Employment dynamics differ substantially across skill groups. Employment in the low-skill sector rises quickly and persistently. The combination of a direct productivity gain in low-skill tasks and an inflow of employed middle-skill workers leads to a significant rise in low-skill employment.[12] The middle-skill sector experiences the deepest contraction. Employment falls on impact and continues to decline as productivity in these tasks deteriorates. Labor supply declines in the middle sector because households re-optimize and either move into low-skill temporary jobs or exit employment to invest in human capital. Once the economy has transitioned, middle-skill employment stabilizes at a level far below its initial steady state. This persistent decline captures the essence of job polarization. High-skill employment exhibits non-monotonic dynamics. It rises initially as high-skill productivity in-

12) This mechanism mirrors empirical evidence that low-skill service occupation employment often expands during polarized technological change.

creases. However, fluctuations appear early in the transition due to slow reallocation of workers. In the long run, high-skill employment increases moderately, but not as dramatically as the population share of high-skill individuals. This occurs because many newly high-skilled households devote more time to training.

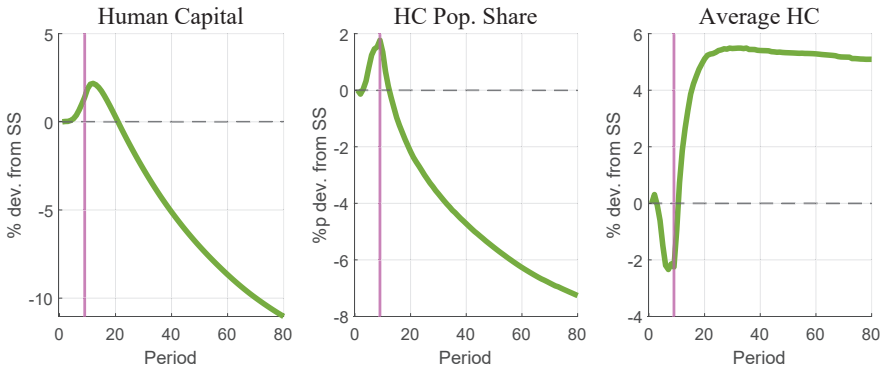
The sectoral outcomes arise from the interaction of two central mechanisms in the model. First, the direct effect of polarized technological progress alters relative productivities across sectors: it lowers the efficiency of middle-skill occupations while raising productivity in both low- and high-skill activities through a higher TFP level. Second, human-capital adjustment is endogenous: workers optimally change their learning and employment decisions in response to these new relative returns, so job polarization is not imposed but emerges from behavior. As a result, the economy undergoes a period of transitional displacement in which many middle-skill workers either remain for a while in declining occupations or move into low-skill jobs before eventually investing in additional human capital and upgrading.[13)]

4. Human-Capital Investment Dynamics

The introduction of polarized technological progress generates complex patterns in human-capital investment, with distinct movements along both the extensive and intensive margins. Figure 3 shows that the economy experiences a pronounced decline in total human-capital investment in the long run. This aggregate effect can be decomposed into (i) the extensive margin—the share of workers who invest in skills—and (ii) the intensive margin—the average human capital of those who do invest. The decline in total investment is driven primarily by the extensive margin. As the premium between low- and middle-skill jobs falls, many households voluntarily choose not to accumulate additional human capital and instead remain in, or move into, relatively better-paying low-skill jobs. With fewer individuals engaging in training, aggregate investment falls. At the same time, the intensive margin rises: among those who do invest, the average level of human capital increases, reflecting an intensification of learning efforts by high-ability or well-positioned workers who

13) Overall, polarized technological change reshapes the sectoral structure mainly through gradual worker reallocation and composition effects. The transition path features a sustained decline in middle-skill employment and persistent increases at both tails of the distribution, capturing the key qualitative features of job polarization.

Figure 3. Human-Capital Investment Dynamics



Note: The figure displays the evolution of total human-capital investment, the share of agents investing in skills, and average human capital among investors. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

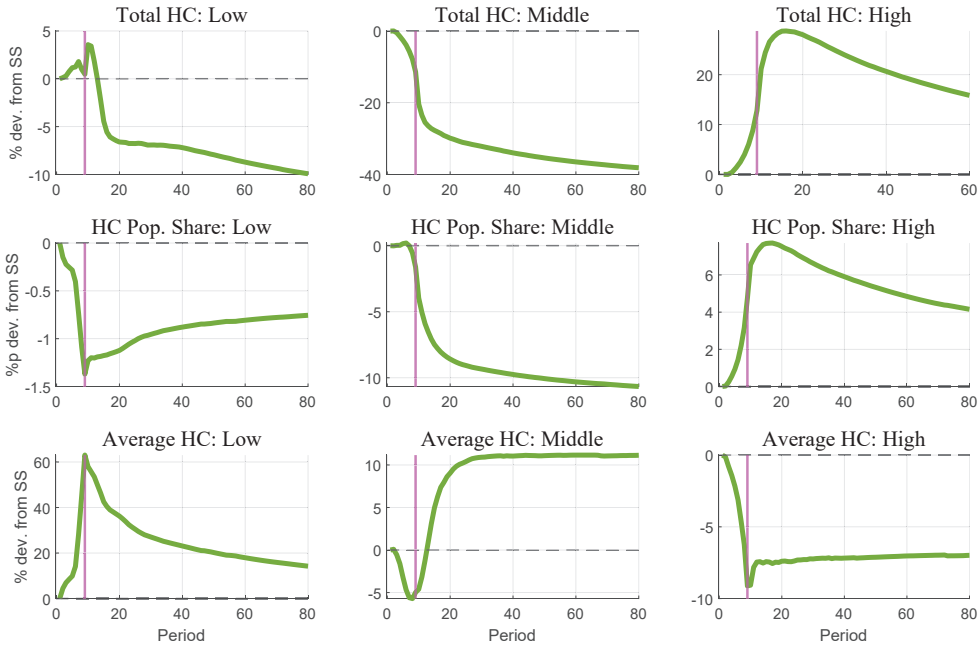
continue to upgrade in response to improved returns at the top of the distribution.

The aggregate human-capital dynamics can be understood by looking at the sectoral patterns. Figure 3 reports the evolution of human capital for low-, middle-, and high-skill households (columns) along three dimensions (rows). The disaggregated responses across skill groups reveal substantial heterogeneity. Among low-skill households, total human-capital investment declines, and the share of individuals engaging in learning also falls. This reflects both limited incentives for very low-skill workers to upgrade rapidly and their reliance on low-skill employment to maintain income. At the same time, those low-skill households that do invest increasingly include inflows from the middle group, so the intensity of investment per investor rises.

In the middle-skill segment, both total human-capital investment and the fraction of households undertaking training decline sharply, as the fall in middle-sector productivity reduces the short-run payoff to investing and many middle-skill workers temporarily move into low-skill jobs before upgrading. However, among the workers who remain in middle-skill occupations, investment becomes more concentrated: they accumulate substantially more human capital, leading to a higher intensive margin of investment within this group.

In contrast, high-skill households display a very different pattern. Their investment initially spikes, reflecting strong incentives to move toward the frontier of

Figure 4. Human-Capital Dynamics by Sectors

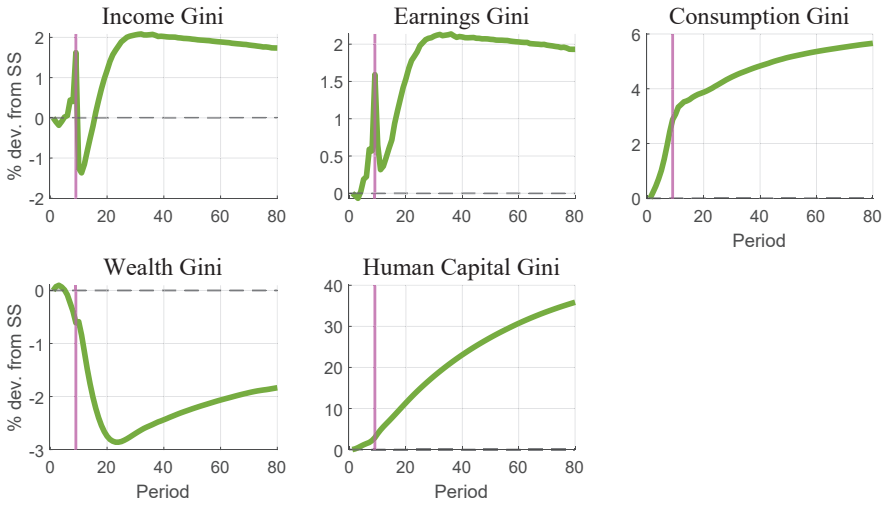


Note: The nine panels report the evolution of human capital for low-, middle-, and high-skill households (columns) along three dimensions (rows). Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

the skill distribution. As high-skill tasks become more productive and command higher earnings, households already positioned near the top of the distribution respond quickly, raising both their investment intensity and their average human-capital levels. However, because the number of high-skill individuals is small, their strong intensive response does not offset the aggregate decline driven by middle-skill households. Moreover, as the transition proceeds, inflows of workers from the middle group enter the high-skill category with relatively low initial human-capital levels. This compositional change pulls down average human capital and investment intensity within the high-skill group, so the eventual decline in average human capital among high-skill workers is best interpreted as a composition effect rather than a weakening of incentives at the top.

In summary, polarized technological progress produces a temporary decline in total human-capital investment, even as average human-capital levels among investors rise. The heterogeneity across skill groups—declining investment in low-

Figure 5. Responses of Key Variables to National Shocks



Note: The figure plots Gini coefficients for income, earnings, consumption, wealth, and human capital along the transition. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

and middle-skill segments and early intensification in the high-skill group—reflects both compositional changes and the underlying incentives embedded in the model's human-capital technology. These dynamics are central for understanding the long-run reallocation of labor and the evolution of inequality in response to polarized technological change.

5. Distributional Outcomes

Polarized technological progress generates rich and gradual distributional dynamics in the economy. Figure 5 illustrates how key inequality measures evolve along the transition path, including the Gini coefficients for income, earnings, consumption, wealth, and human capital. The interplay between labor-market frictions, human-capital accumulation, and employment reallocation produces distinct short-run and long-run movements in each measure, revealing the heterogeneous consequences of structural technological change.

Income and earnings inequality respond strongly to the employment reallocation induced by polarized technological progress. On impact, income inequality falls slightly, as higher wages and a temporary increase in employment draw some

households at the bottom of the distribution into work and compress the lower tail of labor income. Very quickly, however, this effect reverses. As the relative prospects of middle-skill jobs worsen, some workers exit employment to invest in human capital, while others are pushed into lower-paying low-skill occupations. This combination of non-employment spells for workers engaged in skill upgrading and downward occupational mobility widens the dispersion of labor income, and income inequality rises above its initial level. In the long run, income inequality remains persistently higher than in the pre-technology steady state. The wage gap between high-skill workers, who benefit from higher productivity, and workers who remain in low- or middle-skill positions expands, and low-productivity households spend a larger share of their in non-employment while accumulating human capital, keeping their average earnings relatively low.

Consumption inequality moves broadly in parallel with income inequality, but with a smoother profile. Households use savings to partially buffer income fluctuations, so the short-run spike in income dispersion is attenuated. However, incomplete markets prevent full insurance, and the persistent divergence in earnings capacity eventually feeds into consumption. As a result, consumption inequality rises steadily over the transition and remains elevated in the long run.

Polarized technology also affects wealth inequality. The wealth Gini declines slightly as middle-income households increase their precautionary savings in response to labor-market uncertainty and potential periods of non-employment. This precautionary motive temporarily compresses the asset distribution. Finally, human-capital inequality increases markedly in the long run. The decline in middle-skill productivity induces a reallocation of investment effort toward high-skill occupations, but the adjustment is uneven across the population. High-ability and high-wealth households respond quickly to the improved incentives and invest aggressively in skill upgrading, raising their human-capital levels significantly. In contrast, many middle- and low-skill households face financial constraints or limited ability, leading them to postpone or reduce investment. This divergence produces a gradual increase in the dispersion of human capital, which amplifies differences in future earnings and contributes further to long-run income and wealth inequality.

Taken together, these patterns demonstrate that polarized technological progress has substantial and multifaceted distributional consequences. Employment disrup-

Table 4. Welfare Effect by Sectors

Low	Middle	High	Average
3.17	2.80	2.87	2.93

Note: This table reports consumption-equivalent welfare changes (%) for households for low-, middle-, and high-skill in the benchmark economy.

tions generate short-run fluctuations in inequality, while long-run forces—skill-biased wage growth, differential investment incentives, and persistent wealth accumulation—drive a sustained increase in dispersion across all key dimensions of economic status. The resulting inequality dynamics highlight the central role of human-capital frictions and incomplete markets in shaping the distributional impact of structural technological change.

6. Welfare Effects

Polarized technological progress generates heterogeneous welfare effects across the skill distribution, reflecting the differing ways in which households are exposed to productivity changes, labor-market frictions, and human-capital adjustment costs. Table 4 reports welfare changes for households initially located in each skill group, expressed in consumption-equivalent terms.[14] The results reveal clear cross-sectional patterns in welfare gains, consistent with the sectoral and distributional dynamics documented above.

Welfare gains are largest for low-skill households. These individuals benefit from the rise in productivity and wages in the low-skill sector and face relatively little pressure to undertake costly human-capital investment. Because the polarized technology increases the value of tasks at the bottom of the distribution, low-skill workers experience improved earnings prospects without needing to incur large skill-adjustment costs. Their labor-market position strengthens immediately, and their transition path involves minimal disruption. As a result, their welfare gains exceed those of middle- and high-skill groups, despite having lower initial human capital.

High-skill households also experience sizable welfare improvements, though the

14) We measure welfare effects in consumption-equivalent terms (%) by comparing lifetime utility in the initial steady state with lifetime utility in the new steady state.

gains are smaller than those of the low-skill group. The increase in productivity at the top raises long-run wages and enhances the return to human-capital accumulation. These households have both the ability and the resources to take advantage of the more skill-intensive production structure, and they benefit from the long-run expansion of the high-skill sector. However, high-skill workers often undertake additional human-capital investment early in the transition, which temporarily reduces consumption. This initial adjustment cost dampens the magnitude of their welfare gains relative to the low-skill group.

In contrast, welfare gains for middle-skill households are the smallest among the three groups. The decline in middle-skill productivity reduces their earnings immediately, and many experience significant employment disruptions during the transition. At the same time, they face strong incentives to upgrade their skills, but doing so requires costly learning and periods of reduced labor supply. These workers are therefore hit from both sides: they suffer losses in current income while absorbing the penalties associated with human-capital adjustment. Although many eventually transition into higher-productivity occupations, the path to doing so is long and costly. The combination of income losses, learning costs, and temporary non-employment results in modest welfare gains relative to other groups.

Taken together, the welfare analysis confirms that polarized technological progress produces an uneven distribution of benefits across the population. Low-skill households gain the most, high-skill households gain moderately, and middle-skill households gain the least. These differences stem from the interaction between task-specific productivity changes and the frictions that govern skill accumulation and employment adjustment. The results highlight that even when aggregate productivity and output rise, the transitional burden can fall disproportionately on workers in occupations directly exposed to technological displacement. This underscores the importance of understanding transitional dynamics and distributional effects when evaluating the welfare consequences of structural technological change.

7. The Role of Labor-Market Frictions

This subsection examines how labor-market frictions shape the aggregate and distributional consequences of polarized technological progress by comparing the

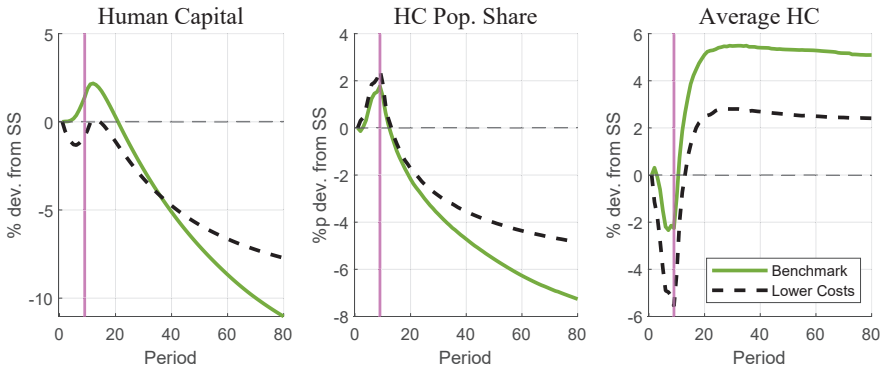
benchmark economy with two counterfactuals that remove them one at a time. The first experiment eliminates frictions in human-capital adjustment, allowing workers to change their skill levels quickly and at low cost. This isolates the extent to which slow and costly re-skilling drives the employment decline, the gradual nature of sectoral reallocation, and the rise in inequality in the benchmark transition. The second experiment removes frictions in firms' employment adjustment, so labor demand can respond immediately to changes in sectoral productivity and workforce composition. Comparing these environments highlights a clear asymmetry: while worker-side frictions in skill accumulation fundamentally alter the depth and distribution of the transition, firm-side adjustment frictions mainly affect the short-run volatility of employment, leaving the main macro and inequality patterns largely intact.

7.1. Effects of Removing Human-Capital Adjustment Costs

To understand the role of human-capital adjustment frictions, we consider a counterfactual economy in which these costs are eliminated. Removing the adjustment cost allows households to alter their skill levels immediately, offering a useful contrast with the gradual and friction-laden transition observed in the benchmark economy. The implications of this experiment are summarized in Figure 7 (aggregates), Figure 6 (human-capital dynamics), and Figure 8 (distributional outcomes).

Figure 6 compares the response of human capital in the benchmark economy with adjustment costs (solid line) to a case with lower human-capital adjustment costs (dashed line). The overall pattern is quite different. In the benchmark, aggregate human capital rises on impact and then declines gradually in a hump-shaped fashion. When adjustment costs are removed, aggregate human capital instead falls slightly on impact and then stays close to its initial steady-state level. This behavior can be decomposed into an extensive margin—the share of workers who invest in skills—and an intensive margin—the average human capital of those who invest. In the zero-cost case, the extensive margin expands: a larger share of households engages in human-capital accumulation. However, many of these new investors enter from relatively low initial human-capital levels, so the intensive margin falls and average human capital drops more sharply on impact. This compositional effect temporarily

Figure 6. Human-Capital Dynamics under No Adjustment Costs



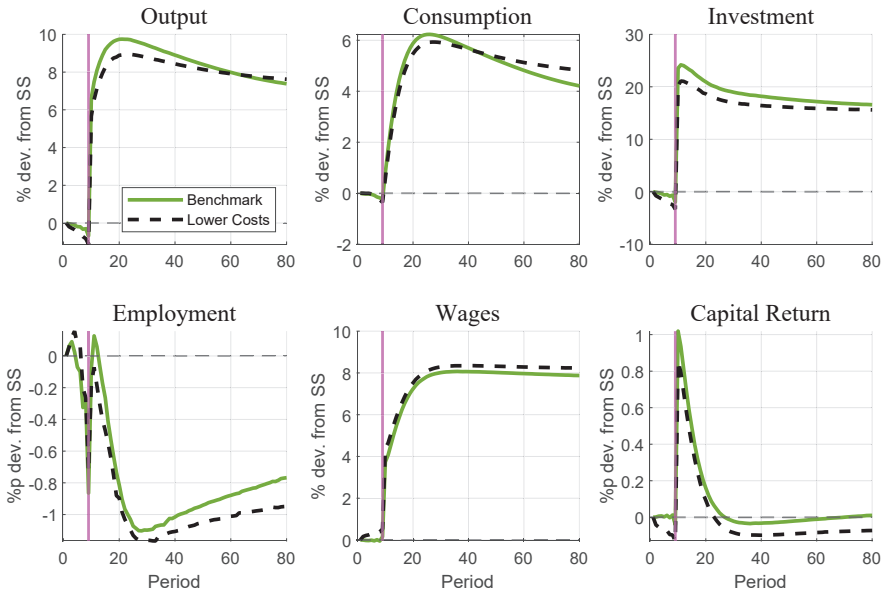
Note: The panels compare total human capital, the share of agents investing, and average human capital in the benchmark (solid) and low-cost (dashed) economies. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

pulls down the aggregate stock of human capital, even though investment is more widespread.

These changes in human-capital dynamics translate into markedly different aggregate outcomes. As illustrated in Figure 7, the key difference arises in employment. In the model without adjustment costs, employment does not drop significantly. Because some workers do not need to leave employment to acquire additional skills when adjustment is frictionless, effective labor supply remains higher throughout the transition, leading to smoother and earlier increases in aggregate quantities. Wages adjust more gradually, reflecting the faster compositional shift toward high-skill labor, and the return on capital stabilizes sooner as firms respond to the improved quality of the labor input.

Distributional outcomes also differ substantially, as shown in Figure 8. Income inequality rises more sharply early in the transition, because high-ability and high-wealth households are able to respond immediately to the new environment and upgrade their skills, moving quickly into high-productivity positions. Over time, however, inequality becomes less volatile than in the benchmark, since the employment response is relatively stable and large non-employment spells among middle-skill workers are largely absent. Wealth inequality behaves somewhat differently. Because middle-skill households no longer face large learning costs or severe income disruptions, their precautionary saving motive weakens, leading to a more

Figure 7. Aggregate Dynamics with and without Human-Capital Adjustment Costs



Note: Solid lines show the benchmark economy; dashed lines show the economy with lower (or zero) human-capital adjustment costs.

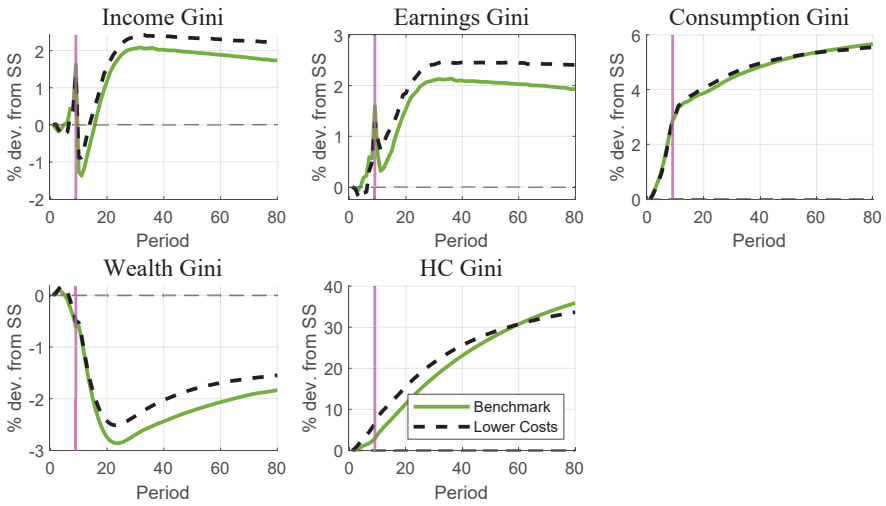
pronounced short-run decline in wealth concentration.

7.2. Effects of Removing Employment Adjustment Costs

We next consider a counterfactual in which firms face no costs when adjusting employment. In the benchmark economy, employment evolves sluggishly because firms incur quadratic penalties when expanding or contracting the workforce. Removing this friction allows labor demand to adjust immediately in response to changes in productivity, wages, and the composition of the workforce. Figures 9 and 10 summarize how this modification affects aggregate dynamics and inequality during the transition under polarized technological progress.

The elimination of employment adjustment costs has surprisingly limited effects on most aggregate variables. As shown in Figure 9, output, consumption, investment, wages, and the return on capital follow paths nearly identical to those in the benchmark model. The reason is that polarized technological progress operates pri-

Figure 8. Inequality Dynamics with and without Human-Capital Adjustment Costs

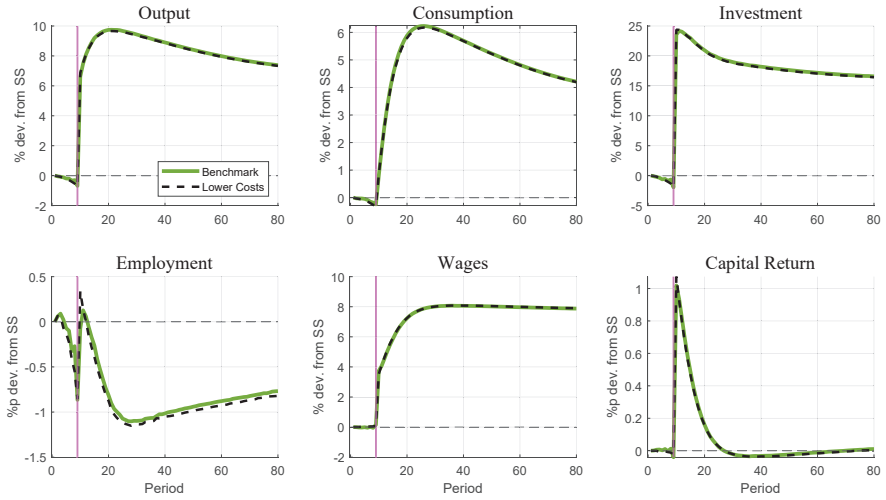


Note: The figure compares Gini coefficients in the benchmark (solid) an no-cost (dashed) economies. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

marily through changes in relative task productivity and the endogenous response of human capital, both of which evolve independently of firms' short-run hiring behavior. Since productivity adjusts exogenously and human-capital dynamics remain governed by household behavior, aggregate quantities continue to transition along almost the same path as in the benchmark.

The main differences appear in the employment dynamics. In the benchmark model, employment initially drops sharply because households temporarily withdraw from the labor market to invest in human capital and because firms respond gradually to changing labor demand. When employment adjustment costs are eliminated, firms no longer smooth labor demand over time. Employment therefore adjusts more sharply and more quickly: the initial decline is deeper, and fluctuations are more volatile, as shown in the employment panel of Figure 9. Without the penalty on hiring or firing, firms immediately reduce employment in sectors where productivity falls, especially middle-skill tasks, and expand employment more rapidly in sectors experiencing rising productivity. These sharper movements reflect a more mechanically responsive labor demand schedule, although they do not

Figure 9. Aggregate Dynamics with and without Employment Adjustment Costs



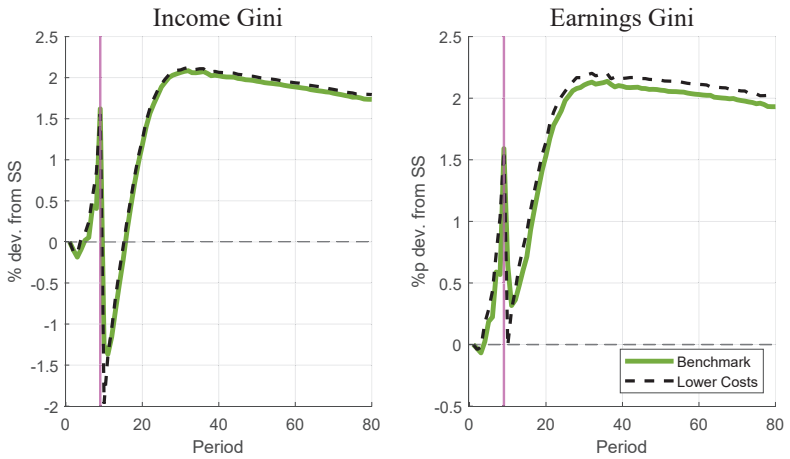
Note: Solid lines show the benchmark economy; dashed lines show the case without employment adjustment costs. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

alter the broader macroeconomic trajectory.

Distributional outcomes, shown in Figure 10, are affected only marginally. Income and earnings inequality still increase during the transition, driven primarily by the compositional shift toward high-skill occupations and the productivity decline in the middle-skill sector. However, the timing of these changes differs slightly from the benchmark. Because employment adjusts more abruptly, the early-period response of income and earnings inequality is steeper, with a more pronounced initial dip followed by a faster rise. This reflects the immediate contraction of middle-skill employment and the instantaneous expansion in low- and high-skill labor demand. As a result, inequality becomes more sensitive to short-run employment movements, but the long-run level of inequality remains nearly unchanged.

Overall, the comparison between the benchmark and the no-cost case shows that employment adjustment frictions play a relatively minor role in shaping the macroeconomic consequences of polarized technological progress. These frictions mainly smooth labor demand and dampen short-run employment volatility but do not materially influence aggregate output, consumption, investment, or wages.

Figure 10. Inequality Dynamics with and without Employment Adjustment Costs



Note: Solid lines show the benchmark economy; dashed lines show the case without employment adjustment costs. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

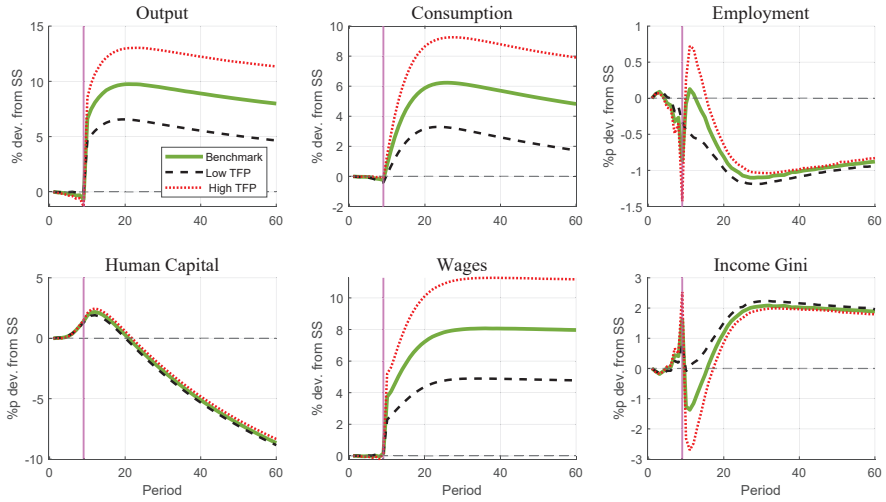
Likewise, their impact on inequality is modest and operates primarily through the timing rather than the magnitude of income dispersion.

8. Sensitivity Analysis

To assess the robustness of the transition dynamics, we conduct two sets of sensitivity analyses: one that varies the magnitude of the technological shock and another that alters the size of penalties associated with human-capital adjustment. These exercises allow us to evaluate whether the main qualitative results depend critically on parameter choices or whether the mechanisms identified in the benchmark model persist across alternative calibrations. The results are summarized in Figure 11 for different TFP sizes and in Figure 12 for different penalty sizes.

Varying the size of the technological shock primarily affects the overall scale of the macroeconomic responses without altering their qualitative features. We compare two cases: a smaller 3% increase in aggregate TFP and a larger 7% increase, holding the polarized structure of technological progress fixed. As shown in Figure 11, a larger TFP increase generates a stronger and more persistent rise in output and consumption, while a smaller increase produces correspondingly weaker responses.

Figure 11. Aggregate Responses to Different Sizes of the Technological Shock



Note: The figure compares transition paths under smaller and larger aggregate TFP increases, holding the structure of polarized technological progress fixed. Two scenarios: a smaller 3% TFP increase and a larger 7% TFP increase. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

Employment follows a similar pattern: although the short-run decline remains a prominent feature of the transition, the magnitude of this decline decreases when the TFP shock is smaller and intensifies when it is larger. Human-capital investment responds proportionally as well. In scenarios with a larger TFP shock, households face stronger incentives to upgrade skills, leading to higher total investment and a faster increase in average human capital. Wages rise more sharply under larger shocks, reflecting the strong productivity effect, and income inequality widens slightly more because the returns to skill become more dispersed. Despite these quantitative differences, the overall transition structure remains intact: the economy still undergoes a short-run adjustment phase characterized by employment reallocation, followed by a long-run expansion driven by capital deepening and skill upgrading.

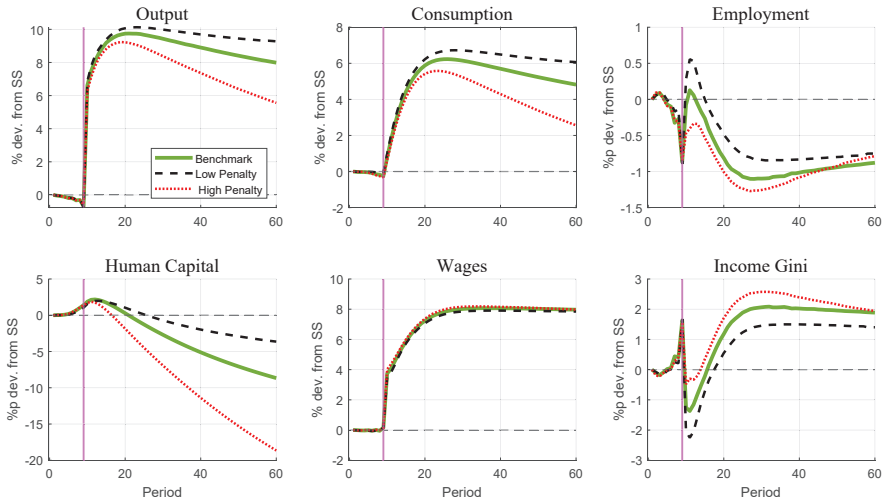
The second part of the sensitivity analysis varies the size of the penalty parameter that governs how strongly the middle-skill sector is disadvantaged. Figure 12 compares aggregate dynamics under a lower penalty (“Low Penalty”) and a higher penalty (“High Penalty”) relative to the benchmark. Specifically, we consider

two cases: a smaller 3% penalty and a larger 7% penalty on middle-skill productivity. When the penalty is smaller, the technology is less strongly polarized against middle-skill tasks. Human capital declines by less, and the economy reorganizes more quickly toward its new production structure. Output and consumption rise more on impact and remain closer to their new steady-state levels throughout the transition. Employment, however, becomes somewhat more volatile: with a weaker penalty, households reallocate more aggressively across occupations and into learning spells, generating a larger short-run swing in labor input. Income inequality increases, but by less than in the benchmark, because the earnings loss for middle-skill workers is attenuated and the gap between middle- and high-skill wages widens more moderately.

By contrast, a higher penalty amplifies the adverse consequences for the middle-skill sector and makes the transition more sluggish. Human capital falls sharply and remains well below its steady-state level for an extended period, as shown in the "High Penalty" path. Output and consumption still rise in the long run, but their short- and medium-run responses are noticeably weaker than in the benchmark. Employment declines more persistently, reflecting both reduced demand for middle-skill labor and slower reallocation into high-skill positions. The compositional shift toward high-productivity tasks unfolds gradually, which also tempers the wage response. In this case, income inequality rises more strongly and peaks at a higher level than in the benchmark, as middle-skill workers suffer larger and more protracted earnings losses while high-skill workers capture most of the productivity gains.

Taken together, the two sensitivity exercises show that the main mechanisms of the model are robust. Varying the size of the technological shock primarily scales the macroeconomic responses: larger TFP gains produce stronger and more persistent increases in output, consumption, human capital, and wages, whereas smaller gains yield correspondingly muted dynamics, without changing the qualitative shape of the transition. Altering the penalty parameter governing the disadvantage of middle-skill tasks mainly affects the intensity and speed of polarization: lower penalties lead to a faster and more growth-friendly reallocation with a more moderate rise in inequality, while higher penalties generate weaker aggregate gains and stronger, more persistent distributional effects. In all cases, however, the economy exhibits

Figure 12. Aggregate Responses under Different Penalty Intensities



Note: Solid lines report the benchmark penalty on middle-skill productivity; dashed and dotted lines show lower and higher penalties. Two cases: a smaller 3% penalty and a larger 7% penalty on middle-skill productivity. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

the same fundamental pattern—a temporary adjustment phase with employment reallocation and human-capital investment, followed by a long-run expansion and a widening of income inequality driven by shifts in the human-capital distribution.

V. Low- or High-Skill-biased Technological Progress

In this section, we compare the benchmark polarized technological progress with other forms of skill-biased technological change. In the benchmark, technology simultaneously raises productivity in the low- and high-skill sectors while reducing productivity in the middle-skill sector, generating a pronounced hollowing-out of middle-skill jobs. To highlight what is specific to this polarized structure, we consider two alternative experiments. The first is a low-skill-biased change, in which productivity gains are concentrated at the bottom of the skill distribution and both middle- and high-skill tasks are penalized. The second is a high-skill-biased change that instead augments productivity primarily at the top, imposing a direct penalty on low- and middle-skill tasks. Comparing aggregate and distributional dynamics

across these three environments allows us to separate the effects of polarization per se from the broader consequences of shifting productivity toward either low- or high-skill workers.

1. Low-skill-biased Technological Change

In this subsection, we instead consider a low-skill-biased technological change in which gains are concentrated at the bottom of the skill distribution.[15] This experiment is useful for contrasting the benchmark polarization scenario with a technology that disproportionately benefits low-skill workers and, therefore, alters both aggregate dynamics and distributional outcomes.[16] Figures 13–16 compare the transition paths in the benchmark (solid line) and low-skill-biased (dashed line) economies.

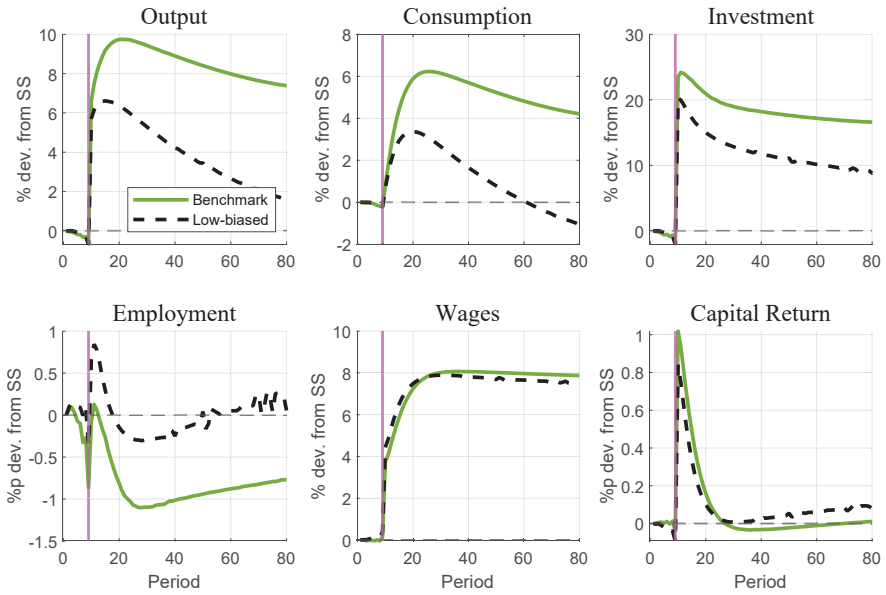
On the aggregate side, low-skill-biased progress delivers smaller but less disruptive macroeconomic effects. Output and investment still rise above their initial steady-state levels i, but the peaks are substantially lower than under polarized progress, and the responses are more muted over the entire transition. At the same time, employment does not exhibit the pronounced and persistent decline observed in the benchmark. Instead, aggregate employment slightly increases after the shock and stays close to its initial level. Because the technological improvement directly raises the productivity of existing low-skill jobs, workers have less need to leave employment in order to accumulate human capital. As a result, the economy avoids the deep short-run contraction associated with middle-skill displacement and intensive retraining in the benchmark case. Wages and the return on capital still jump on impact, reflecting higher marginal products of labor and capital, consistent with the long-run productivity gain.

Sectoral employment patterns highlight the different nature of job reallocation in this scenario. As shown in Figure 14, employment of low-skill workers rises strongly

15) Specifically, we keep the aggregate TFP increase at 5%, but impose a 2.5% productivity penalty on the middle and high sectors—half of the sectoral adjustment used for the middle group in the polarized benchmark. We view this as a fairer comparison than assigning a full 5% change to each sector, because it preserves the same overall TFP gain while moderating the degree of sectoral distortion. In any case, our interpretation of these experiments is primarily qualitative rather than quantitative.

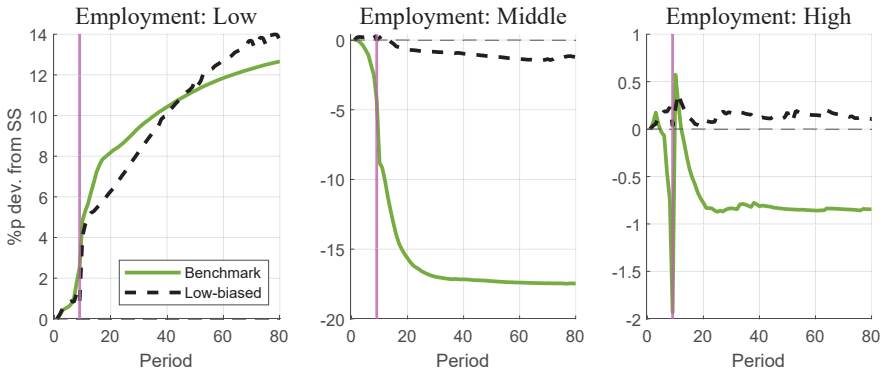
16) This scenario is meant to capture technologies that disproportionately benefit low-skill tasks, such as route-optimizing apps, handheld scanners, or platform algorithms that raise the productivity of couriers, warehouse pickers, or ride-hail drivers. It thus provides a useful contrast to the benchmark polarization case in terms of both aggregate dynamics and distributional outcomes.

Figure 13. Aggregate Dynamics under Low-Skill-Biased Technological Progress



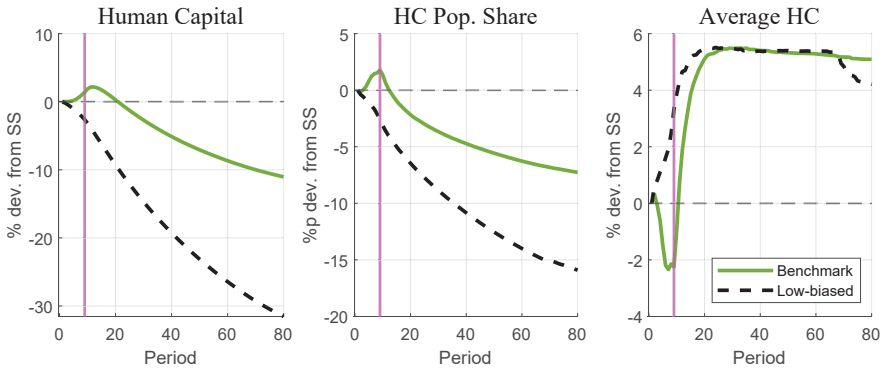
Note: Solid lines show the benchmark polarized case; dashed lines show the low-skill-biased technology. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

Figure 14. Sectoral Employment under Low-Skill-Biased Technological Progress



Note: The panels show population shares and employment levels by skill group relative to the initial steady state. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

Figure 15. Responses of Key Variables to National Shocks

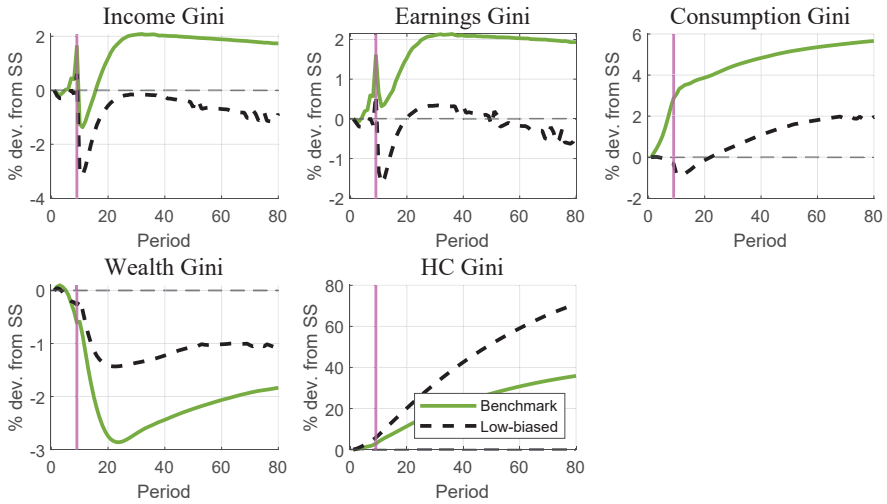


Note: The figure compares Gini coefficients in the benchmark and low-skill-biased economies. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

and persistently, and the increase is even larger than in the benchmark case. The middle-skill sector still contracts, but the decline is much milder: employment falls only modestly and stabilizes well above the sharply depressed level observed under polarized technological progress. High-skill employment increases only slightly and remains close to its initial level. This is becausemiddle- and high-skill workers have less need to leave employment in order to accumulate human capital. Thus, low-skill-biased technology does not generate a pronounced hollowing-out of the middle. Instead, it produces a tilt of the employment structure toward low-skill tasks, with a relatively modest compression of middle-skill employment and only limited expansion at the top. Put differently, the economy becomes more bottom-heavy rather than polarized,.

The human-capital responses are almost the mirror image of those in the benchmark. In the polarized case, rising returns to high-skill tasks induce strong incentives to upgrade, lifting both the stock of human capital and the share of high-skill workers. Under low-skill-biased progress, by contrast, the aggregate stock of human capital declines over the transition, and the population share of high-skill workers falls markedly below the benchmark path. Because low-skill productivity rises and high-skill premia shrink, the payoff to costly skill upgrading diminishes. Many workers find it optimal to remain in or move into the better-paying low-skill sector rather than undertake expensive training. Average human capital among those who

Figure 16. Inequality under Low-Skill-Biased Technological Progress



Note: The figure compares Gini coefficients in the benchmark and low-skill-biased economies. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

do invest still increases, reflecting selection into learning by relatively high-ability households, but this intensive-margin response is dominated by a sharp decline in the extensive margin—the number of individuals choosing to upgrade. The long-run economy under low-skill-biased progress therefore operates with less overall human capital and a smaller high-skill workforce than in the benchmark.

These changes in skill incentives and employment patterns translate into markedly different distributional outcomes. Figure 16 shows that income, earnings, and consumption inequality increase far less under low-skill-biased progress. Because the productivity gains accrue primarily to low-skill workers, earnings dispersion across the bottom and middle of the distribution narrows, and the overall income Gini rises only slightly relative to the benchmark. Consumption inequality also increases only modestly, as improvements in low-skill earnings help households at the bottom smooth shocks more effectively. At the same time, however, wealth and human-capital inequality rise more in the low-biased scenario. Wealth inequality also ends up higher than in the benchmark. Even though low-skill households enjoy higher wages, the strongest asset accumulation occurs among the small group of high-skill workers who retain large earnings advantages and face little competition from up-

wardly mobile middle-skill households.

Overall, the low-skill-biased experiment underscores a key trade-off. Redirecting technological gains toward low-skill tasks reduces the need for costly reallocation and dampens the rise in labor-income and consumption inequality, but it also weakens incentives for human-capital accumulation, lowers long-run output relative to the benchmark, and ultimately produces greater dispersion in both human capital and wealth. In this sense, low-skill-biased progress can be viewed as more inclusive in the short run—it protects and even improves the position of low-skill workers and mitigates middle-skill displacement—but at the cost of slower skill upgrading and weaker long-run growth compared with polarized technological progress.

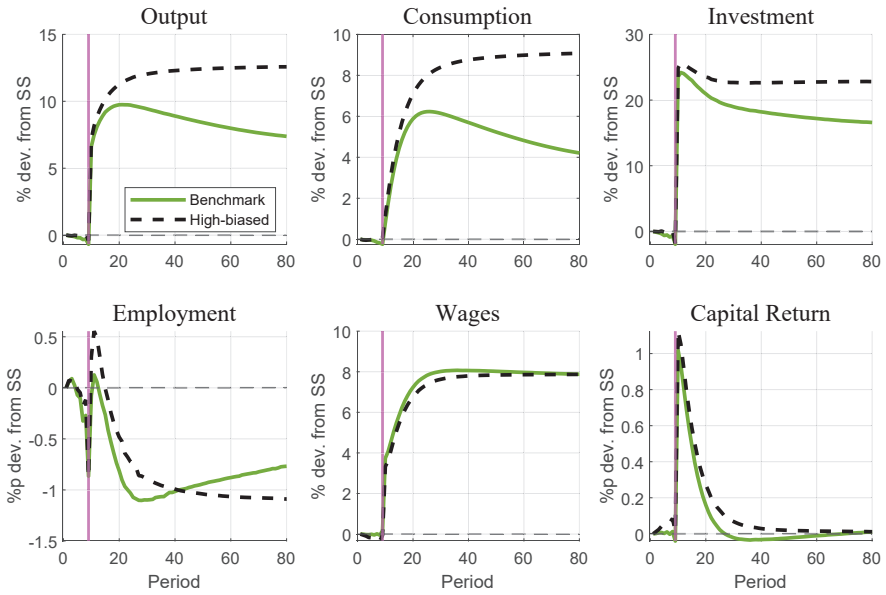
2. High-skill-biased Technological Change

In this subsection, we instead consider a high-skill-biased technological change in which the productivity gains are concentrated entirely in the high-skill sector.[17] This experiment isolates the consequences of directing new technology toward the very top of the skill distribution, and it provides a useful contrast with the benchmark polarized scenario. This type of technological progress can be interpreted as high-end design suites that raise the productivity of architects, mechanical engineers, or chip designers, or as advanced imaging technologies, robotic surgery systems, and clinical decision-support tools that primarily enhance the productivity of doctors and specialist nurses. Figures 17–20 compare the resulting transition path (dashed line) with the benchmark economy (solid line). Ffor this kid of tech progree is intertpeteda s High-end design suites that increase the productivity of architects, mechanical engineers, chip designers, etc. Imaging technologies, robotic surgery systems, clinical decision support tools that primarily raise productivity of doctors and specialist nurses.

On the aggregate side, high-skill-biased progress produces stronger, but not qualitatively different, macro outcomes than in the benchmark. Output, consumption, and investment all rise by more and remain persistently above the benchmark paths throughout the transition, so the economy enjoys larger long-run gains in real

17) As before, we keep the aggregate TFP increase at 5%, but now impose a 2.5% productivity penalty on the middle- and low-skill sectors.

Figure 17. Aggregate Dynamics under High-Skill-Biased Technological Progress

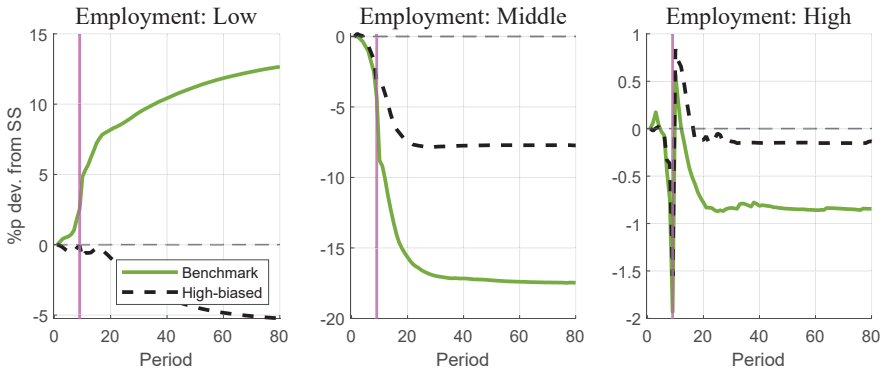


Note: Solid lines denote the benchmark polarized case; dashed lines denote high-skill-biased technology. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

activity when new technology is targeted to high-skill tasks. However, aggregate employment dynamics are quite similar to those in the polarized case: employment still declines over the transition and settles below its initial level, with only modest quantitative differences. Wages and the return on capital also move very similarly in the two scenarios, displaying a sharp initial increase followed by gradual convergence to their new steady states.

Aggregate employment dynamics are not very different from the benchmark, but the sectoral patterns change sharply. Sectoral employment dynamics reveal how high-skill bias reorders the occupational structure. In the benchmark polarized case, low-skill employment expands strongly and persistently, the middle-skill sector collapses, and high-skill employment eventually declines. Under high-skill-biased progress, this pattern changes markedly. Low-skill employment now remains essentially flat, with at most a small decline relative to the initial steady state, because the productivity of low-skill tasks does not improve and firms have little rea-

Figure 18. Sectoral Employment under High-Skill-Biased Progress

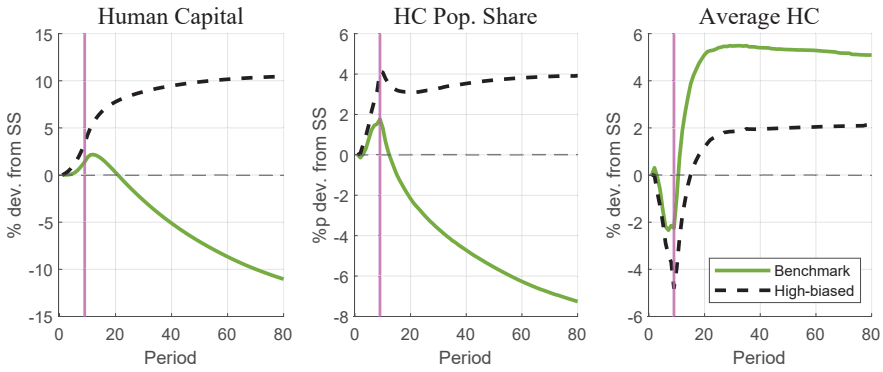


Note: Solid lines denote the benchmark polarized case; dashed lines denote high-skill-biased technology. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

son to expand hiring at the bottom. Middle-skill employment still contracts, but the decline is much milder: employment stabilizes after a moderate drop of about 6 percent instead of the nearly 20 percent contraction observed under polarized progress. High-skill employment, by contrast, no longer drifts downward; it quickly returns to a level close to its original steady state. In combination, these movements imply that high-skill-biased technology produces a more top-heavy employment structure—preserving high-skill jobs while avoiding the extreme hollowing-out of middle-skill employment seen in the benchmark.

Human-capital dynamics respond even more strongly to high-skill bias. Figure 18 shows that the aggregate human-capital stock rises sharply and persistently in the high-biased case, whereas it declines in the benchmark. The share of the population classified as high-skill increases by several percentage points relative to the initial steady state and remains above the benchmark path for the entire transition. Because the returns to high-skill tasks rise substantially, households across the distribution find it attractive to upgrade, and the extensive margin of human-capital investment expands. At the same time, average human capital—measured relative to the total number of workers—rises less in the high-biased scenario than in the benchmark. This reflects the fact that many additional workers move into the high-skill group; the marginal entrants have lower underlying ability or financial resources than the initial high-skill core, so the average human capital per worker increases more slowly

Figure 19. Sectoral Human Capital under High-Skill-Biased Progress



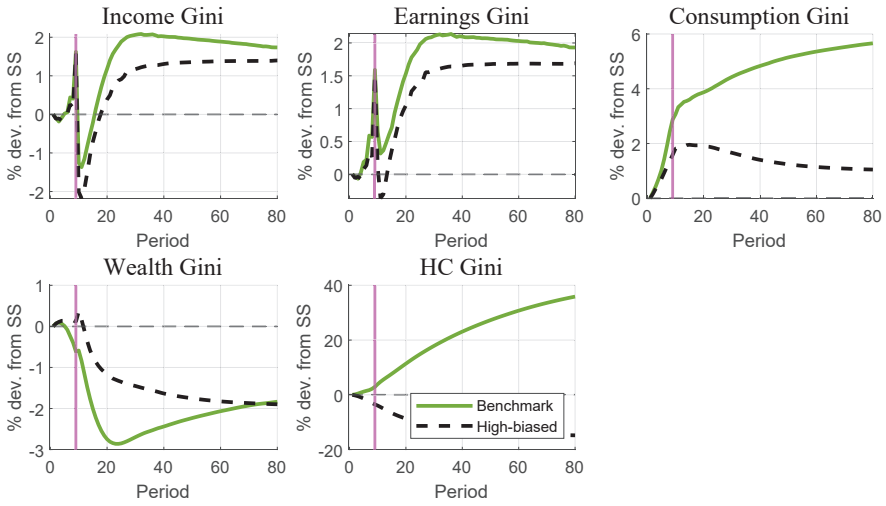
Note: Solid lines denote the benchmark polarized case; dashed lines denote high-skill-biased technology. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

even though the total stock grows rapidly. In other words, the scale of skill upgrading is larger under high-skill bias, but the intensity per skilled worker is somewhat lower.

These differences in skill accumulation and sectoral employment translate into distinctive distributional outcomes. Income and earnings Gini coefficients still rise in response to high-skill-biased progress, but the increase is smaller than in the benchmark. This is particularly interesting and somewhat counterintuitive: because middle-skill employment remains higher than under polarized progress, the job-polarization effect is mitigated. Consumption inequality behaves even more favorably. Unlike in the benchmark, where the consumption Gini increases steadily, high-skill-biased technology leaves consumption inequality roughly unchanged, or even slightly lower than in the initial steady state. Improved earnings prospects for workers who successfully upgrade, combined with smoother employment dynamics in the middle of the distribution, allow households to better stabilize consumption despite ongoing structural change.

Human-capital inequality exhibit particularly striking contrasts. Under the benchmark polarized shock, the human-capital Gini rises sharply as only a subset of households invests aggressively and the middle group is squeezed. In the high-biased case, by contrast, the human-capital Gini falls relative to the initial steady state. The reason is that the strong incentive to upgrade induces many middle-skill workers to accumulate skills and join the high-skill sector, compressing the dispersion of

Figure 20. Inequality under High-Skill-Biased Technological Progress



Note: Solid lines denote the benchmark polarized case; dashed lines denote high-skill-biased technology. Time is annual. The vertical line marks the ten-year anticipation phase before implementation of the technology.

human capital even though the overall level rises. .

Overall, the high-skill-biased experiment shows that directing technological progress primarily toward high-skill tasks can generate larger aggregate gains and more intensive human-capital upgrading, while avoiding some of the most adverse distributional outcomes associated with polarized progress. Output, consumption, and investment expand more strongly, and the occupational distribution shifts toward higher skills without an extreme collapse of middle-skill employment. At the same time, income and earnings inequality still rise, but by less than in the benchmark, and both human-capital and consumption inequality are actually lower in the long run. In this sense, high-skill-biased technological change delivers stronger growth and more widespread upgrading of skills, while moderating the rise in inequality that accompanies polarized technological progress.

A direct comparison with the low-skill-biased case highlights how redirecting the same aggregate technological gain across sectors changes both macro and distributional outcomes. Under low-skill-biased progress, aggregate output, consumption, and investment rise by less than in the polarized benchmark and the high-skill-biased case, but low-skill employment expands strongly and persistently, and income

and consumption inequality increase only modestly. In contrast, high-skill-biased progress delivers larger and more sustained gains in output and consumption, while stabilizing middle-skill employment at a higher level than under polarized progress.

Human-capital dynamics also move in opposite directions. Low-skill-biased progress reduces the aggregate human-capital stock and raises human-capital and wealth inequality, as workers have weaker incentives to upgrade and many remain in relatively well-paid low-skill jobs. High-skill-biased progress instead induces broad-based upgrading, with a sizable increase in the number of high-skill workers, a higher aggregate stock of human capital, and a lower human-capital Gini relative to the benchmark. Thus, low-skill bias is more favorable to low-skill workers and delivers the smallest rise in income and consumption inequality, but at the cost of slower skill accumulation and weaker long-run growth, whereas high-skill bias promotes intensive skill upgrading and stronger growth while generating a moderate increase in earnings dispersion—larger than under low-skill bias but smaller than under polarized progress.

VI. Conclusion

This paper has examined how new technological progress interacts with labor-market frictions, human-capital accumulation, and inequality in an economy calibrated to Korean data. We developed a heterogeneous-agent general equilibrium model with incomplete markets, endogenous skills, and frictions in both labor supply and employment adjustment. Workers choose between full-time employment and time-intensive learning, while firms face costs when changing their workforce. Calibrated to match key Korean moments in employment, training, and the joint distribution of income and wealth, the model provides a disciplined laboratory for studying long-run transitions under different patterns of technological change.

The benchmark polarized technological shock raises productivity in low- and high-skill tasks while reducing it in middle-skill activities. It is growth-enhancing but employment-saving: output, consumption, investment, and wages rise in the long run, yet aggregate employment falls as workers reallocate time from market work to human-capital accumulation. The economy converges to a more skill-intensive structure with higher living standards but fewer hours worked.

These aggregate gains come with significant distributional costs. Middle-skill employment shrinks, low- and high-skill segments expand, and many middle-skill workers either move into low-skill jobs or exit employment to retrain, generating earnings losses and higher consumption risk. Income and consumption inequality rise, wealth becomes more concentrated, and the human-capital distribution fans out as high-ability and high-wealth households upgrade first.

The key bottleneck is worker-side frictions in human-capital adjustment rather than firm-side hiring rigidities. When skill upgrading is easier, employment does not fall and aggregates adjust more smoothly, even though inequality still increases. Comparing polarized, low-skill-biased, and high-skill-biased progress shows that which tasks technology favors critically shapes the trade-off between growth, skill upgrading, and inequality. For economies with rigid labor markets and high retraining costs, this points to two central policy levers: easing human-capital frictions (adult training, income support during retraining, portable credentials) and steering the direction of technological progress through R&D and industrial policy.

Several extensions would further enhance the framework's relevance. One natural step is to introduce explicit policy instruments—training subsidies, unemployment or wage insurance, or skill-contingent transfers—to evaluate which interventions best mitigate transitional inequality without unduly dampening innovation and growth. For instance, training subsidies could facilitate skill upgrading, while unemployment or wage insurance could cushion short-run income losses from displacement. Skill-contingent transfers could further address distributional imbalances between winners and losers of technological progress. Embedding these instruments would make it possible to assess the trade-off between equity and efficiency, identifying policies that mitigate inequality without significantly dampening innovation and growth. A second avenue is to endogenize the direction of technological change by allowing innovators to choose which tasks to augment, so that sectoral productivity paths respond to prices, policies, and political constraints. Third, incorporating richer labor-market institutions—such as dual contracts, unions, or search and matching frictions—would allow the model to capture additional features of the Korean labor market, including the divide between regular and non-regular workers.

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Appendix

A. Computational Procedure for the Quantitative Model

In this appendix, we describe in detail how we compute the steady-state equilibrium and the transition dynamics of the model. The procedure follows the standard approach in the heterogeneous-agent quantitative macroeconomic literature, adapted to the specific structure of our environment with human capital accumulation.

A.1. Steady-State Equilibrium

In the steady state, the cross-sectional distribution of households, denoted by $\mu(a,h,z)$, and the factor prices are time-invariant. A stationary equilibrium consists of: (i) a set of value and policy functions for households, (ii) a stationary distribution μ over individual states, and (iii) factor prices (r,w) consistent with firms' first-order conditions and aggregate resource constraints. We proceed as follows.

1.1. Discretization of the individual state space

We discretize the individual state space along three dimensions: the risk-free asset a, human capital h, and the idiosyncratic labor productivity z. Let N_a, N_h, and N_z denote the number of grid points for each variable. In the baseline computation, we set

$$N_a = 151, \quad N_h = 151, \quad N_z = 9.$$

The grids for a and h are constructed to capture behavior near the borrowing and low-human-capital regions with high resolution, while still spanning the relevant support of the stationary distribution:

- For the asset grid, we choose a lower bound $a_{\min}$ at 0 and an upper bound $a_{\max}$ large enough so that the stationary distribution essentially puts no mass at the upper endpoint. We then place grid points on $[a_{\min}, a_{\max}]$ using a non-linear transformation so that the density of grid points is higher near $a_{\min}$, where the consumption–savings decision is most sensitive to changes in wealth.

- For the human capital grid, we use an analogous construction on $[h_{\min}, h_{\max}]$. We choose $h_{\min}$ strictly positive and $h_{\max}$ sufficiently large to cover the range of realized human capital in the stationary distribution. As with assets, we concentrate grid points near the lower part of the support to better capture the nonlinearity of human capital accumulation and its interaction with borrowing constraints.

Formally, we obtain ordered grids $\{a_i\}_{i=1}^{N_a}$ and $\{h_j\}_{j=1}^{N_h}$, which will be used for value function iteration and integration over the distribution.

1.2. Discretization of idiosyncratic productivity and transition matrix

Idiosyncratic labor productivity z follows an AR(1) process in logs as described in the main text. We approximate this continuous process by a finite-state Markov chain $\{z_k\}_{k=1}^{N_z}$ with an associated transition matrix $\pi(z' \mid z)$. We choose $N_z = 9$ grid points for z, equally spaced over the symmetric interval

$$\left[-\frac{3\sigma_z}{\sqrt{1-\rho_z^2}}, \frac{3\sigma_z}{\sqrt{1-\rho_z^2}} \right],$$

where ρ_z is the persistence parameter and σ_z is the standard deviation of the innovation. This range covers approximately three unconditional standard deviations of the stationary distribution of the AR(1) process.

To construct the transition probability matrix $\pi(z' \mid z)$, we use the discretization Tauchen (1986)'s method. This yields a Markov chain with the desired persistence and variance properties, which we then hold fixed throughout the computation.

1.3. Solution of the household problem and computation of policy functions

Given a candidate vector of parameters and factor prices (r, w), we solve the household's dynamic programming problem defined on the grid $\{(a_i, h_j, z_k)\}$. For each state (a_i, h_j, z_k), the household chooses next-period assets $a'(a_i, h_j, z_k)$ and human capital $h'(a_i, h_j, z_k)$, subject to the budget constraint, borrowing limits, and the law of motion for human capital.

We solve for the value function $V(a,h,z)$ and the associated policy functions in the following way:

1. *Initialization.* We start with an initial guess for the value function $V^{(0)}(a_i,h_j,z_k)$, for example the value function from a simpler problem (no shocks) or a constant function.

2. *Bellman operator.* Given $V^{(n)}$, we compute the right-hand side of the Bellman equation at each grid point to obtain $V^{(n+1)}$ The maximization is performed subject to the constraints on a' and h' and the discretized grids. When the optimal a' and h' do not lie exactly on the grid, we employ interpolation or a discrete search over feasible grid points, depending on computational convenience.

3. *Numerical optimization.* For the maximization step, we either conduct a discrete search over the (a',h') grid or use a continuous optimization routine combined with interpolation over the value function. In practice, a combination of coarse discrete search with local refinement works well. For each state, we store the argmax, yielding policy functions $a'(a_i,h_j,z_k)$ and $h'(a_i,h_j,z_k)$.

4. *Convergence.* We iterate on the Bellman operator until the value function converges. Specifically, we stop the iteration when the sup norm between successive iterates satisfies

$$\max_{i,j,k}\left|V^{(n+1)}(a_i,h_j,z_k)-V^{(n)}(a_i,h_j,z_k)\right|<\varepsilon_V,$$

   where ε_V is a small tolerance level. At convergence, we obtain the fixed point $V(a_i,h_j,z_k)$ and the corresponding stationary policy functions $a'(a_i,h_j,z_k)$ and $h'(a_i,h_j,z_k)$.

The result of this step is a set of decision rules that map each individual state (a,h,z) into next-period choices (a',h') given the steady-state prices (r,w).

1.4. Computation of the stationary distribution $\mu(a,h,z)$

Given the decision rules and the Markov process for z, we compute the stationary, time-invariant cross-sectional measure $\mu(a,h,z)$. This distribution describes the

fraction of households at each point in the individual state space in the steady state.

We proceed as follows:

1. *Initialization of the distribution.* We start from an initial guess $\mu^{(0)}(a_i, h_j, z_k)$. This can be a degenerate distribution (e.g., all mass at a particular point) or a uniform distribution over the grid. We normalize it so that

$$\sum_{i,j,k} \mu^{(0)}(a_i, h_j, z_k) = 1.$$

2. *Forward iteration using the law of motion.* Given $\mu^{(n)}$ and the policy functions, we construct $\mu^{(n+1)}$ by applying the implied transition of individual states:

   - For each current state (a_i, h_j, z_k), the decision rules specify next-period choices (a', h'), and the Markov chain for z gives the probabilities of moving to $z_{k'}$.
   - We map (a', h') back to the nearest grid points (or interpolate the distribution across neighboring points) and use the transition probabilities $\pi(z_{k'} \mid z_k)$ to distribute the mass $\mu^{(n)}(a_i, h_j, z_k)$ over next-period states $(a_{i'}, h_{j'}, z_{k'})$.

   This yields an updated distribution $\mu^{(n+1)}$ that respects the law of motion induced by optimal behavior and the exogenous shock process.

3. *Convergence to a fixed point.* We repeat this procedure until the distribution converges in the L^1 or sup norm:

$$\sum_{i,j,k} \left| \mu^{(n+1)}(a_i, h_j, z_k) - \mu^{(n)}(a_i, h_j, z_k) \right| < \varepsilon_\mu.$$

   At convergence, we obtain a stationary distribution $\mu(a_i, h_j, z_k)$ that is invariant under the joint dynamics of (a, h, z).

Given μ, we compute aggregate quantities by integrating over the state space, for example:

$$K = \sum_{i,j,k} a_i \, \mu(a_i, h_j, z_k), \qquad L = \sum_{i,j,k} \ell(a_i, h_j, z_k) \, \mu(a_i, h_j, z_k),$$

where $\ell(a,h,z)$ denotes effective labor supplied by a household with state (a,h,z) under the optimal policy.

1.5. Market clearing and parameter adjustment

Given the stationary distribution and the policy functions, we compute aggregate capital K and effective labor L, and then determine factor prices (r,w) from firms' first-order conditions. We check whether these prices are consistent with the ones used to solve the household problem:

- If the implied factor prices and aggregates match the targeted steady-state objects (e.g., capital–output ratio, interest rate, wage level, or moments of the wealth and income distributions) within a specified tolerance, we have found a steady-state equilibrium.
- If not, we update the parameters or the guess for (r,w) and repeat steps 3–5. In practice, we use a root-finding or fixed-point algorithm (such as bisection or Newton-type methods) on the discrepancy between implied aggregates and targets to search for the parameter or price vector that ensures consistency.

This outer loop continues until both individual optimality and aggregate consistency conditions are jointly satisfied, yielding the steady-state equilibrium.

A.2. Transition Dynamics

We now describe the computation of transition dynamics from an initial steady state (e.g., the status quo policy) to a new steady state (e.g., after a permanent policy change). The transition path is computed under the assumption that the policy change is fully anticipated at $t = 1$, and that the economy converges to the new steady state by a finite horizon T.

2.1. Initial and final steady states

We first compute:

$$(\mu^0, r^0, w^0, K^0, L^0) \quad \text{and} \quad (\mu^\star, r^\star, w^\star, K^\star, L^\star),$$

the initial steady state under the baseline policy and the new steady state under the new policy regime, respectively. These are obtained using the steady-state procedure outlined in Section A .1 with the appropriate parameter values and policy rules. The two steady states provide boundary conditions for the transition.

2.2. Time horizon and discretization of the transition path

We assume that the economy reaches (or gets arbitrarily close to) the new steady state after T periods. In the baseline parameterization, we set $T = 100$, and interpret one period as one year. Thus, we compute a 100-year transition path.

We construct time paths for aggregate variables and prices:

$$\{K_t, L_t, r_t, w_t\}_{t=1}^{T},$$

with the boundary conditions $(K_1, L_1) = (K^0, L^0)$ and $(K_T, L_T) \approx (K^\star, L^\star)$.

2.3. Initialization of aggregate paths and factor prices

We initialize a guess for the time paths of the capital–labor ratio $\{K_t/L_t\}_{t=2}^{T-1}$. A simple starting point is a linear interpolation between the initial and final steady states, but other monotone paths can be used as well. Given this path, we construct sequences of factor prices $\{r_t, w_t\}_{t=2}^{T-1}$ using firms' first-order conditions in each period, with (r_1, w_1) and (r_T, w_T) anchored at the steady-state values (or very close to them).

These sequences of prices are taken as given by the households when we solve their dynamic problem along the transition path.

2.4. Backward induction for value and policy functions along the transition

Since the terminal steady state is known, we can solve the household problem along the transition path via backward induction:

1. *Terminal condition at $t = T$.* At time T, we set the value function $V_T(a, h, z)$ equal to the steady-state value function associated with the new regime, or solve a

one-period problem using the terminal prices (r_T, w_T) if we treat T as the last period.

2. *Backward recursion from $t = T-1$ to $t = 1$.* Given V_{t+1} and factor prices (r_t, w_t), we solve the household's dynamic programming problem at date t for each state (a,h,z). As in the steady-state computation, we enforce borrowing and other constraints and use numerical optimization or grid search to obtain policy functions $a'_t(a,h,z)$ and $h'_t(a,h,z)$ for each t. We repeat this step backward for $t = T-1, T-2, \ldots, 1$, obtaining a full sequence of value functions and policy functions $\{V_t, a'_t, h'_t\}_{t=1}^{T}$.

This backward step ensures that at each date t, households correctly internalize both current and future factor prices as well as the stochastic evolution of productivity.

2.5. Forward iteration for the distribution $\{\mu_t\}_{t=1}^{T}$

Given the policy functions $\{a'_t, h'_t\}$ and the Markov chain for z, we compute the sequence of cross-sectional distributions along the transition path:

1. *Initial distribution at $t = 1$.* We set the initial measure μ_1 equal to the stationary distribution from the initial steady state μ^0.

2. *Forward iteration.* For each $t = 1, 2, \ldots, T-1$, we construct μ_{t+1} from μ_t using the law of motion for individual states implied by the policy functions and the shock process. As before, we move mass across the (a,h,z) grid using policy functions and the transition matrix $\pi(z' \mid z)$, with interpolation if necessary. This generates a sequence $\{\mu_t\}_{t=1}^{T}$ consistent with optimal behavior and the assumed path of factor prices.

The outcome of this step is the full time path of the distribution of households over (a,h,z) during the transition.

2.6.Aggregation of macroeconomic variables along the transition

Using the distributions $\{\mu_t\}$ and policy functions at each date, we compute the implied aggregate variables:

$$K_t = \sum_{i,j,k} a_i \, \mu_t(a_i, h_j, z_k), \qquad L_t = \sum_{i,j,k} \ell_t(a_i, h_j, z_k) \, \mu_t(a_i, h_j, z_k),$$

as well as output, consumption, investment, government revenues, and any other aggregates of interest. These aggregates can also be used to verify resource constraints and to compute welfare along the transition path.

The resulting sequences $\{K_t, L_t\}_{t=1}^{T}$ represent the model-implied transition given the initial guess for the capital–labor ratio and the associated prices.

2.7. Updating the aggregate paths and convergence

Finally, we check whether the implied sequences $\{K_t, L_t\}$ are consistent with the assumed paths used to construct factor prices:

- We compare the updated $\{K_t/L_t\}$ with the initially assumed $\{K_t/L_t\}$. If the absolute differences are below a predetermined tolerance for all t, the transition path has converged. In this case, the sequences $\{\mu_t, K_t, L_t, r_t, w_t\}_{t=1}^{T}$ form an equilibrium transition from the initial to the new steady state.

- If not, we update the guessed path of $\{K_t/L_t\}$ using a relaxation or damping scheme, for example:

$$\left(\frac{K_t}{L_t}\right)^{\text{new}} = \lambda \left(\frac{K_t}{L_t}\right)^{\text{implied}} + (1-\lambda)\left(\frac{K_t}{L_t}\right)^{\text{old}},$$

  for some $\lambda \in (0, 1]$, and return to step 3. This "shooting" or "time-iteration" procedure is repeated until the aggregate paths converge.

Once convergence is achieved, we obtain a fully consistent transition path that respects individual optimality, market clearing, and the laws of motion for the exogenous processes, providing the basis for all quantitative transition results reported in the paper.

⟨Abstract in Korean⟩

신기술의 도입이 한국 경제의 성장, 고용 및 불평등에 미치는 영향

마은성*, 최기산**

본 연구는 인공지능(AI), 자동화 등 신기술의 도입이 노동시장 마찰과 상호작용하면서 한국 경제의 성장, 고용 및 불평등에 어떠한 영향을 미치는지를 분석하였다. 이를 위해 불완전시장 환경에서 가계가 노동을 공급하거나 학습을 통해 인적자본을 축적하는 선택을 하는 이질적 경제주체 일반균형 모형을 구축하였다. 기업은 자본과 유효노동을 결합하여 생산하며, 고용을 조정할 때 이차형(quadratic) 비용을 부담하도록 설정하였다. 분석 결과, 양극화적(polarized) 기술진보 충격이 발생할 경우 장기적으로 산출, 소비, 투자 모두 증가하지만, 가계가 노동공급을 줄이고 인적자본 축적에 더 많은 시간을 배분함에 따라 총고용은 감소하는 것으로 나타났다. 이러한 노동시간의 재배분은 숙련 집단 간의 내생적인 일자리 양극화를 초래하며, 그 결과 소득 및 소비 불평등이 확대된다. 또한 노동시장 마찰은 이러한 효과의 규모와 지속 기간을 결정하는 핵심 요인으로 작용하는데, 특히 숙련 조정 속도가 느리고 조정 비용이 클수록 기술 전환기에 나타나는 고용 감소와 분배 격차가 더욱 확대되는 것으로 나타났다. 마지막으로 본 연구는 기술 변화가 산업 및 숙련 측면에서 어떤 집단에 상대적으로 유리하게 작용하는지에 따라 거시경제 성과와 불평등의 전개 양상이 달라질 수 있음을 보였다.

핵심 주제어: 기술진보, 노동시장 마찰, 인적자본 축적, 일자리 양극화

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