AI and Human Capital Accumulation: Aggregate and Distributional Implications*

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Abstract

This paper examines how anticipated advances in artificial intelligence (AI) – which compress middle-skill wage premia but increase returns to high-level expertise – reshape human capital investment, labor supply, saving, and inequality. We build an incomplete-markets model with endogenous human capital and asset accumulation in general equilibrium, featuring three skill sectors and uninsurable idiosyncratic risk. We characterize household's behavior using a two-period version, then calibrate an infinite-horizon model to U.S. data. Our findings reveal that AI induces a *voluntary job polarization* through both human capital investment and labor supply choices, reallocating workers away from the middle toward both tails. Human capital adjustments amplify AI's positive effects on aggregate output and consumption while dampening its impact on employment. These adjustments also raise income and consumption inequality but mitigate the rise in wealth inequality that AI advancements would otherwise generate.

Keywords: AI, Job Polarization, Human Capital, Inequality

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1 Introduction

A defining feature of recent AI advancements is their ability to perform complex, cognitive, non-routine tasks – capacities that once required substantial education and expertise. This fundamental difference sets AI apart from earlier waves of automation or computerization, which primarily replaced manual or routine labor.[1] In this paper, we make a central assumption – supported by a growing body of evidence – that AI adoption reduces the premium for middle-level skills while increasing the value of high-level expertise. Based on this assumption, we construct an incomplete markets economy with endogenous asset accumulation and general equilibrium to study how AI's effects on skill premia interact with households' human capital investment, and their subsequent impact on aggregate and distributional outcomes of the economy.

1.1 Evidences for AI's effects on skill premia

Recent labor market data highlight the disproportionate impact of AI on entry-level employment opportunities. Bloomberg (2025) reports that, in the words of Matt Sigelman, president of the Burning Glass Institute, "Demand for junior hires in many college-level roles is already declining, even as demand for experienced hires in the same jobs is on the rise." According to Revelio Labs (2025), postings for entry-level jobs in the US declined by about 35% since January 2023, with roles more exposed to AI experiencing even steeper reductions.

Recent experimental evidence reviewed by Calvino *et al.*, (2025) shows that workers' productivity gains from AI depend on their skill levels and experience. On simpler tasks where AI performs well, the technology can narrow the productivity gap between experienced and less experienced workers. However, for more complex tasks that AI cannot yet perform effectively, those with greater digital proficiency or task-specific experience achieve higher productivity gains, as successful use of AI in these settings requires more advanced skills and experience that involves understanding AI's capabilities and limitations.

Firm-level evidence reveals similar patterns. Aghion *et al.*, (2019) documents that the average worker in low-skilled occupations receives a significant wage premium when employed by a more innovative firm. Souza (2025) finds that the adoption of AI in Brazilian firms increases employment for low-skilled production workers but reduces employment and wages for middle-wage office workers. Asam and Heller (2025) report that GitHub Copilot enables software startups to raise initial funding 19% faster with 20% fewer developers, and that these productivity gains disproportionately benefit startups with more experienced founders.

[1]For example, AI tools in medical diagnostics now assist radiologists in analyzing medical images, potentially reducing demand for entry-level radiologists while simultaneously increasing the productivity of senior professionals.

In anticipation of these changes, households are likely to adjust their human capital investments. A 2022 report by Higher Education Strategy Associates finds that following decades of growth, dropping student enrollment in higher education has become a major trend in the Global North (Higher Education Strategy Associates, 2022). In the U.S., the public across the political spectrum has increasingly lost confidence in the economic benefits of a college degree.[2]

On the other hand, demand for sector-based training and reskilling opportunities has been rising. The Oliver Wyman Forum (2024) study documents widespread and significant gaps between employees' desire for reskilling in generative AI and the opportunities their employers are willing to offer. The study estimates that, over the coming decade, billions of workers will need upskilling and millions may require complete reskilling.

1.2 Overview of our model and results

We consider an economy with three sectors, each requiring low, middle, or high levels of skill (human capital) and exhibiting increasing labor productivity. Households can invest in human capital to move up to more productive sectors; without such investment, their skills depreciate, causing them to shift toward less productive sectors over time. Human capital investment occurs at two levels: a basic level achievable while working, and a higher level that demands full-time commitment, such as pursuing higher education or reskilling training. Households face uninsurable idiosyncratic productivity shocks, affecting both their labor productivity and the returns to human capital investment.

We model AI advancements as increasing the productivity for the low and high sectors but not for the middle sector so that the skill premium of the middle sector decreases and the skill premium of the high sector increases.

Using a two-period partial equilibrium model, we show that the effects of AI on skill premia discourage human capital investment for households in the low sector and encourage human capital investment for households in the middle sector, thereby increasing human capital inequality. Human capital investment via full-timing training crowds out households' labor supply so that households in the low sector supplies more labor whereas households in the high sector supplies less labor, in response to the AI advancements.

We also examine how human capital investment interacts with saving decisions. When households are able to adjust their human capital, changes in skill premia affect their exposure to idiosyncratic risk, since moving between sectors alters the level of their labor income. As AI reduces the skill premium for the middle sector,

[2]Pew Research Center reports that about half of Americans say having a college degree is less important today than it was 20 years ago in a survey conducted in 2023 (Pew Research Center, 2024). A 2022 study from Public Agenda (2022), a nonpartisan research organization, shows that young Americans without college degrees are most skeptical about the value of higher education.

households in the low sector face less idiosyncratic risk and consequently decrease their precautionary saving. In contrast, because AI increases the skill premium for the high sector, households in the high sector become more exposed to risk and therefore increase their saving. For households in the middle sector, the effect of AI on saving is ambiguous.

At the economy level, the effects of AI advancements depend on the sectoral redistribution of households and the general equilibrium effects via wage and capital return responses. We quantify these effects using a fully-fledged dynamic quantitative model that incorporates an infinite horizon, endogenous asset accumulation, and general equilibrium. The model is calibrated to reflect key features of the U.S. economy, capturing realistic household heterogeneity. The steady state distribution of human capital without AI advancements pins down the sectoral distribution of households. We then introduce fully anticipated AI advancements happening in the near future and study the transition dynamics from the current state of the economy to the eventual new steady state.

Our quantitative model demonstrates that AI induces a *voluntary job polarization* through both human capital investment and labor supply choices. A substantial share of middle-sector households voluntarily reallocate to either the low or high sectors in the new steady state via human capital adjustments. During the transition, human capital accumulation becomes increasingly concentrated among a smaller segment of the population, reflecting growing inequality in skill acquisition. In addition to these population shifts, labor supply dynamics further contribute to job polarization: many middle-sector households reduce their labor supply as they engage in full-time training to upskill more rapidly, while labor supply in the low sector rises more than in the high sector.

Building on these labor dynamics, our model investigates how AI shapes the economy's aggregate and distributional outcomes through both its direct impact on sectoral productivity and the endogenous adjustments in human capital investment. To highlight these mechanisms, we compare the transition dynamics of our benchmark model – where households can adjust their human capital – with those of a counterfactual model where human capital remains fixed at its initial steady state.

Our findings reveal that human capital responses to AI amplify its positive effects on aggregate output and consumption, but mitigate its positive effect on employment. While AI's direct effect on sectoral productivity reduces income and consumption inequalities, job polarization resulting from human capital adjustments reverses this effect and increases both inequalities.

Regarding households' saving, the indirect effect of AI through human capital adjustments has little impact on aggregate savings – both in terms of steady state and during the transition. However, these adjustments have a substantial impact on the distribution of wealth: while AI's direct effect increases wealth inequality, the indirect effect from human capital responses partially offsets this increase.

1.3 Related Literature

This paper relates to the literature on how technological change, including AI and robotics, drives job polarization and affects the demand and supply of labor. Studies find that rising employment in both high- and low-wage occupations – at the expense of middle-skill jobs – characterizes job polarization across the UK, US, and Western Europe (Goos and Manning, 2007; Autor and Dorn, 2013; Goos *et al.*, 2014). Robots and automation have also been shown to reduce employment and wages across US regions (Acemoglu and Restrepo, 2020), with automation-induced job losses and declining labor force participation especially concentrated among vulnerable workers in highly automated sectors (Lerch, 2021; Faber *et al.*, 2022). Wang and Wong (2025) models AI as a learning-by-using technology and predicts large productivity gains and employment loss in the long-run.

Technological disruption also influences human capital accumulation. Faced with employment risks caused by automation, many affected workers invest in further education as a form of self-insurance, rather than relying solely on increases in the college wage premium (Atkin, 2016; Beaudry *et al.*, 2016). Consistent with this, Di Giacomo and Lerch (2023) and Dauth *et al.*, (2021) find that the adoption of industrial robots in the U.S. and Germany, respectively, has led to increased college and university enrollments.

Building on this literature, our paper develops a model that explicitly allows for a trade-off between labor supply and human capital investment. In our framework, job polarization emerges as a voluntary response to AI advancements: households in the middle sector may choose to either downskill to the low sector or upskill to the high sector, while an increasing number of middle-sector households opt for full-time training to accelerate their upskilling.

This paper also relates to the literature that studies human capital and physical capital in a unified framework. Chanda (2008) shows that the rise in returns to education reduces household savings. Waldinger (2016) finds that human capital is much more important than physical capital for innovation in both the short and long-run. Huggett *et al.*, (2011) develops a risky human capital model with incomplete markets to estimate the source of lifetime inequality. Park (2018) investigates whether capital and human capital are over-accumulated in an incomplete market economy. Our model is most similar to Huggett *et al.*, (2011) in that human capital is risky and there is a trade-off between human capital investment and labor supply. Our analysis sheds light on the effect of AI-induced human capital adjustments on households labor supply and saving.

A growing body of literature suggests that AI and automation may contribute to rising inequality across income, consumption, and wealth (e.g., Sachs and Kotlikoff, 2012; Berg *et al.*, 2018; Prettner and Strulik, 2020; Hémous and Olsen, 2022). Our model confirms that AI advancements indeed increase inequality in all three dimensions. However, we find that the endogenous human capital responses to AI amplify the rise in income and consumption inequality, while at the same time mitigating the increase in wealth inequality.

The rest of the paper is organized as follows. Section 2 describes the model environment. Section 3 solves the household's problem using a two-period version of the model. Section 4 solves the fully-fledged quantitative model and calibrates it to fit key features of the U.S. economy, including employment rate, human capital investment, and household heterogeneity. Section 5 incorporates AI into the quantitative model and examines its impacts on human capital adjustments. Section 6 analyzes the aggregate and distributional effects of AI. Section 7 concludes.

2 Model Environment

Time is discrete and infinite. There is a continuum of households. Each household is endowed with one unit of indivisible labor and faces an idiosyncratic labor productivity shock, z, and an idiosyncratic learning-ability shock, y. The labor productivity shock follows an AR(1) process in logs:

$$\ln z' = \rho_z \ln z + \varepsilon_z, \varepsilon_z \overset{\text{iid}}{\sim} N(0, \sigma_z^2) \tag{1}$$

The learning-ability shock follows an AR(1) process in logs:

$$\ln y' = \rho_y \ln y + \varepsilon_y, \varepsilon_y \overset{\text{iid}}{\sim} N(0, \sigma_y^2) \tag{2}$$

Households observe (z_t, y_t) at the beginning of each period before making decisions. The asset market is incomplete following Aiyagari (1994), and the physical capital, a, is the only asset available to households to insure against idiosyncratic labor income risk. Households can also invest in human capital, h, which allows them to work in sectors with different human capital requirement.

2.1 Production Technology

The production technology in the economy is a constant-returns-to-scale Cobb-Douglas production function:

$$F(K, L) = K^{1-\alpha} L^{\alpha} \tag{3}$$

K represents the total physical capital accumulated by households, while L denotes the total effective labor supplied by households, aggregated across three sectors: low, middle, and high. The marginal products of capital and effective labor determine the economy-wide wage rate, w, and interest rate, r.

These sectors differ in their technologies for converting labor into effective labor units and in the levels of human capital required for employment. The middle sector employs households with human capital above h_M and converts one unit of labor to one effective labor unit. The high sector, requiring human capital above h_H, converts one unit of labor to $1+\lambda$ effective units, while the low sector, with no human capital requirement, converts one unit into $1-\lambda$ effective units. This implies a sectoral labor productivity $x(h)$ that is a step function in human capital:

$$x(h) = \begin{cases} 1-\lambda & \text{low sector if } h < h_M \\ 1 & \text{middle sector if } h_M < h < h_H \\ 1+\lambda & \text{high sector if } h > h_H \end{cases} \tag{4}$$

A household i who decides to work thus contributes $z_i x(h_i)$ units of effective labor, where z_i is his idiosyncratic productivity. Denote $n_i \in \{0,1\}$ as the indicator that takes one if the household works and zero if the household does not. The aggregate labor is

$$L = \int n_i z_i x(h_i) di, \tag{5}$$

assuming perfect substitutability of effective labor across the three sectors.

2.2 Household's Problem

Households derive utility from consumption, incur disutility from labor and effort of human capital investment. A household maximizes the expected lifetime utility by optimally choosing consumption, saving, labor supply and human capital investment each period, based on his idiosyncratic shocks (z_t, y_t):

$$\max_{\{c_t, a_{t+1}, n_t, e_t\}_{t=0}^{\infty}} E_0 \left[\sum_{t=0}^{\infty} \beta^t (\ln c_t - \chi_n n_t - \chi_e e_t) \right] \tag{6}$$

where c_t represents consumption, a_{t+1} represents saving, $n_t \in \{0,1\}$ is labor supply, and e_t is the effort of human capital investment.

If a household decides to work in period t, he will be employed into the appropriate sector according to his human capital h_t and receive labor income $w_t z_t x(h_t)$. The household's budget constraint is

$$c_t + a_{t+1} = n_t(w_t z_t x(h_t)) + (1+r_t)a_t \tag{7}$$

$$c_t \geq 0 \text{ and } a_{t+1} \geq 0 \tag{8}$$

We prohibit households from borrowing $a_{t+1} \geq 0$ to simplify analysis.[3]

[3] According to Aiyagari (1994), a borrowing constraint is necessarily implied by present value

Human capital investment can take three levels of effort: $\{0, e_L, e_H\}$. A non-working household is free to choose any of the three effort levels but a working household cannot devote the highest level of effort e_H, reflecting a trade-off between working and human capital investment. Hence:

$$e_t \in \{0, e_L, (1 - n_t)e_H\}. \tag{9}$$

Its contribution to next-period human capital is subject to the learning-ability shock:

$$h_{t+1} = y_t e_t + (1 - \delta_h)h_t \tag{10}$$

where δ_h is human capital's depreciation rate. We interpret $y_t e_t$ as effective human-capital investment, with y_t capturing a learning-ability shock.[4]

3 Household Decisions in a Two-Period Model

In this section, we solve the household's problem with two periods to gain intuition.

Period-2 decisions Households do not invest in human capital or physical capital in the last period. The only relevant decision is whether to work.

The household works $n = 1$ if and only if $z \geq \overline{z}(h, a)$, with $\overline{z}(h, a)$ defined as

$$\ln(w\overline{z}(h, a)x(h) + (1 + r)a) - \chi_n = \ln((1 + r)a) \tag{11}$$

The household faces a trade-off between earning labor income and incurring the disutility of working. Given the sector-specific productivity $x(h)$ specified in (4), the threshold for idiosyncratic productivity, $\overline{z}(h, a)$, takes on three possible values:

$$\overline{z}(h, a) = \begin{cases} \overline{z}(a)\frac{1}{1-\lambda} & \text{if } h < h_M \\ \overline{z}(a) & \text{if } h_M \leq h < h_H \\ \overline{z}(a)\frac{1}{1+\lambda} & \text{if } h > h_H \end{cases} \tag{12}$$

$$\text{where } \overline{z}(a) := \frac{(\exp(\chi_n) - 1)(1 + r)a}{w} \tag{13}$$

Households with higher human capital is more likely to work, whereas households with higher physical capital is less likely to work.

Period-1 decisions In addition to labor supply, period-1 decisions include saving and human capital investment, both of which are forward-looking and affected by

budget balance and nonnegativity of consumption. Since the borrowing limit is not essential to our analysis, we set it to zero for simplicity.

[4]Separating y_t from the labor productivity shock z_t introduces an additional state variable relative to the special case in which learning ability is perfectly correlated with labor productivity. In the quantitative model, we discretize (z_t, y_t) jointly (allowing for correlation if desired).

the idiosyncratic risk associated with the productivity shock z'. Our model also features a trade-off between human capital investment and labor supply as a working household cannot devote the highest level of effort e_H in human capital investment. Therefore, human capital investment grants households the possibility of a discrete wage hike in the future but may entail a wage loss in the current period.

To see the implication of this trade-off and how it interacts with uninsured idiosyncratic risk, we proceed in two steps. We first derive the period-1 decisions without uncertainty by assuming that z' is known to the household at period 1 and z' is such that the household will work in period 2. We then reintroduce uncertainty in z' and compare the decision rules with the case without uncertainty.

3.1 Period-1 Labor Supply and Human Capital Investment

3.1.1 Consumption and saving without uncertainty

The additive separability of household's utility implies that labor supply n and human capital investment e enters in consumption and saving choices only via the intertemporal budget constraint:

$$\begin{aligned} c + \frac{c'}{1+r'} &= (1+r)a + n(wzx(h)) + \frac{w'z'x(h')}{1+r'} \\ \text{with } h' &= ye + (1-\delta)h. \end{aligned}$$

The log utility in consumption implies the optimality condition:

$$c' = \beta(1+r')c. \tag{14}$$

Combining it with the budget constraint, we obtain the optimal consumption as a function of labor supply n and human capital investment e:

$$c(n,e) = \frac{1}{1+\beta}\left[(1+r)a + n(wzx(h)) + \frac{w'z'x\left(h' = ye + (1-\delta)h\right)}{1+r'}\right]. \tag{15}$$

3.1.2 Labor supply and human capital investment

The optimal consumption rules in (15) and (14) allow us to express the household's problem as the maximization of an objective function in labor supply n and human capital investment e:[5]

$$\max_{n,e}(1+\beta)\ln c(n,e) - \chi_n n - \chi_e e \tag{16}$$

This maximization depends critically on the household's current human capital and achievable next-period human capital. Accordingly, we partition households into

[5]This follows since $c' = \beta(1+r')c$, so $\ln c' = \ln\beta + \ln(1+r') + \ln c$.

three ranges of h: $[0, h_M(1-\delta)^{-1})$, $[h_M(1-\delta)^{-1}, h_H(1-\delta)^{-1})$, and $[h_H(1-\delta)^{-1}, h_{\max}]$.

We now derive the decision rules for households $h \in [0, h_M(1-\delta)^{-1})$ in detail, as the decision rules for the other two ranges are similar. Conditional on a given learning ability y, we define two cutoffs in human capital:

$$\underline{h}_M(y) := \frac{h_M - ye_H}{1-\delta}, \quad \overline{h}_M(y) := \frac{h_M - ye_L}{1-\delta} \tag{17}$$

These cutoffs divide households into three groups based on their ability to be employed in the middle sector in the next period.

Non-learners are households with $h < \underline{h}_M(y)$. They cannot achieve $h' > h_M$ with either e_L or e_H level of human capital investment today. As a result, they will choose not to invest in human capital, $e = 0$, and their future sectoral productivity will be $x(h') = 1 - \lambda$. These non-learners work $n = 1$ if and only if $z \geq \overline{z}^L_{non}(a)$:

$$\overline{z}^L_{non}(a) = \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1-\lambda)}{1+r'}]}{w} \tag{18}$$

Slow learners are households with $h \in (\underline{h}_M(y), \overline{h}_M(y))$. These households can reach $h' > h_M$ in the next period only by investing $e = e_H$ today. Their choice is restricted to $e = 0$ or $e = e_H$, since selecting $e = e_L$ incurs a cost without any future benefit. Slow learners must trade off between working and human capital investment: choosing $e = e_H$ requires not working today ($n = 0$), while opting to work means forgoing investment in human capital ($n = 1, e = 0$).[6]

Slow learners prefer $(n = 1, e = 0)$ to $(n = 0, e = e_H)$ if and only if $z \geq \overline{z}^L_{slow}(a)$:

$$\overline{z}^L_{slow}(a) = \frac{(\exp(\frac{\chi_n - \chi_e e_H}{1+\beta}) - 1)[(1+r)a + \frac{w'z'}{1+r'}] + \lambda\frac{w'z'}{1+r'}}{w} \tag{19}$$

Fast learners are households with $h > \overline{h}_M(y)$. They can achieve $h' > h_M$ in the next period if they invest $e = e_L$ today. In this case, there is no need to exert high effort e_H in human capital investment. The fast learners choose among three options: $(n = 1, e = 0)$, $(n = 1, e = e_L)$, and $(n = 0, e = e_L)$.[7]

The decision rule for fast learners are as follows:

$$n(z,h,a), e(z,h,a) = \begin{cases} n = 1, e = 0 & \text{if } z \geq \overline{z}^L_{fast}(a) \\ n = 1, e = e_L & \text{if } \underline{z}^L_{fast}(a) \leq z < \overline{z}^L_{fast}(a) \\ n = 0, e = e_L & \text{if } z < \underline{z}^L_{fast}(a) \end{cases} \tag{20}$$

[6]The choice between $(n = 0, e = e_H)$ and $(n = 0, e = 0)$ does not depend on z. For e_H to be relevant, λ must be large enough so that $(n = 0, e = e_H)$ is preferred to $(n = 0, e = 0)$. See the Appendix for details on the lower bound for λ.

[7]Similar to the case of slow learners, the choice between $(n = 0, e = e_L)$ and $(n = 0, e = 0)$ does not depend on z. Moreover, since our model is set up so that $(n = 0, e = e_H)$ dominates $(n = 0, e = 0)$, it implies that $(n = 0, e = e_L)$ dominates $(n = 0, e = 0)$.

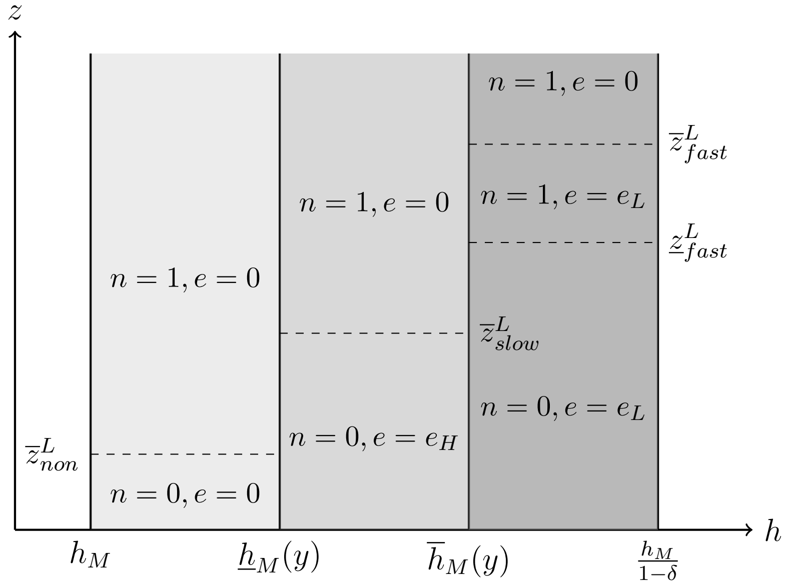


Figure 1: Decision Rule Diagram for $h_M \leq h < h_M(1-\delta)^{-1}$

Conditional on a given learning ability y, the figure illustrates the decision rule (n, e) as a function of states (z, h, a) for households with $h_M \leq h < h_M\frac{1}{1-\delta}$. The human capital h changes along the horizontal axis and the labor productivity shock z changes along the vertical axis. The two vertical lines $\underline{h}_M(y)$ and $\overline{h}_M(y)$ defined in (17) separate the state space into non-learners, slow learners, and fast learners. Within each learner type, labor supply and investment choices vary with z through cutoffs $\overline{z}^L_{non}(a)$, $\overline{z}^L_{slow}(a)$, $\underline{z}^L_{fast}(a)$, and $\overline{z}^L_{fast}(a)$.

where

$$\overline{z}^L_{fast}(a) = \frac{\left\{\exp(\frac{\chi_e e_L}{1+\beta})\lambda\left[\exp(\frac{\chi_e e_L}{1+\beta}) - 1\right]^{-1} - 1\right\}\frac{w'z'}{1+r'} - (1+r)a}{w} \tag{21}$$

$$\underline{z}^L_{fast}(a) = \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'}{1+r'}]}{w} \tag{22}$$

We set up our model so that $\overline{z}^L_{fast}(a) > \underline{z}^L_{fast}(a)$.[8]

Decision rule diagram: With a separate learning-ability shock y, the decision rule (n, e) depends on the state (z, y, h, a). Conditional on y, the cutoffs in h are given by (17). Figure 1 illustrates how labor supply and investment choices vary with (h, z) conditional on a given y.

This decision rule diagram is representative for households in other four ranges of human capital. Figure 2 illustrates the regions in which households are able to make positive human capital investments that move them across sectoral thresholds. Dark shading denotes regions in which e_L is sufficient (fast learners), while light shading

[8] Appendix A.2 provides the parameter restrictions such that the condition for $(n = 0, e = e_H)$ to dominate $(n = 0, e = 0)$ is sufficient for $\overline{z}^L_{fast}(a) > \underline{z}^L_{fast}(a)$.

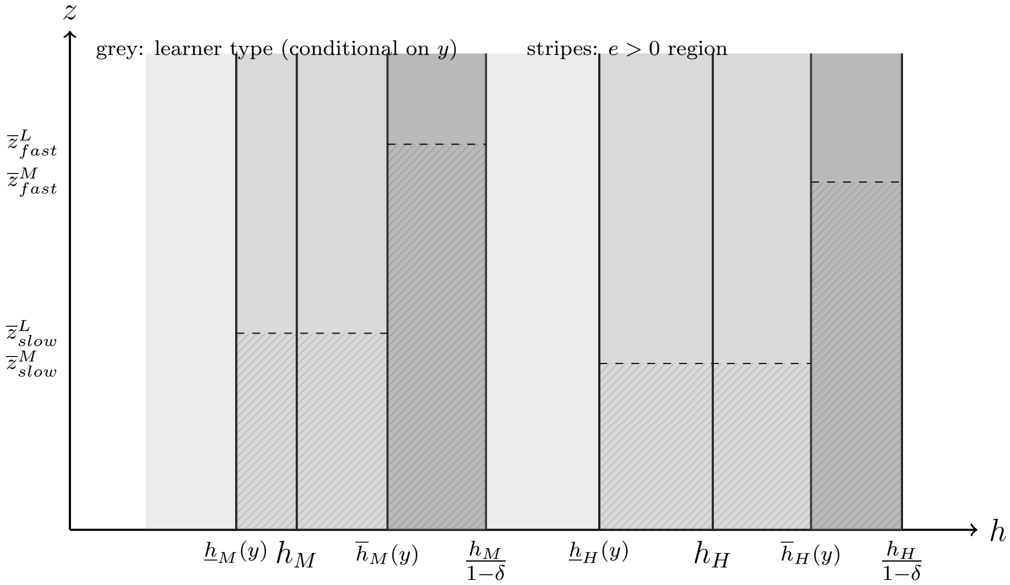


Figure 2: State Space for Human Capital Investment

With a separate learning-ability shock y, the figure illustrates the (h, y) regions in which households can raise next-period human capital above h_M or h_H. Dark shading indicates that e_L is sufficient to cross the relevant threshold (fast learners), while light shading indicates that only e_H is sufficient (slow learners).

denotes regions in which only e_H is sufficient (slow learners).

For households with $h < h_M$, the current sector is low and $x(h) = 1 - \lambda$. Conditional on y, the cutoffs $\underline{h}_M(y)$ and $\overline{h}_M(y)$ continue to separate non-learners, slow learners and fast learners. Note that the threshold h_M itself can lie in any of the three regions depending on y: $h_M < \underline{h}_M(y)$ (all $h < h_M$ are non-learners), $\underline{h}_M(y) \leq h_M < \overline{h}_M(y)$ (some $h < h_M$ are slow learners), or $h_M \geq \overline{h}_M(y)$ (some $h < h_M$ are fast learners). Since low-sector labor income is scaled by $1 - \lambda$, the cutoffs in z are adjusted by $\frac{1}{1-\lambda}$, i.e., $\overline{z}^L_{non}\frac{1}{1-\lambda}$, $\overline{z}^L_{slow}\frac{1}{1-\lambda}$, $\underline{z}^L_{fast}\frac{1}{1-\lambda}$, and $\overline{z}^L_{fast}\frac{1}{1-\lambda}$.

For households with $h_M\frac{1}{1-\delta} \leq h < h_H\frac{1}{1-\delta}$, conditional on y the boundaries for state space division change to $\overline{h}_H(y)$ and $\underline{h}_H(y)$:

$$\underline{h}_H(y) := \frac{h_H - ye_H}{1-\delta}; \qquad \overline{h}_H(y) := \frac{h_H - ye_L}{1-\delta} \tag{23}$$

If $h_M\frac{1}{1-\delta} \leq h < h_H$, the four cutoffs that partition the decision regions for households are denoted as $\overline{z}^M_{non}(a)$, $\overline{z}^M_{slow}(a)$, $\underline{z}^M_{fast}(a)$, and $\overline{z}^M_{fast}(a)$ (see Appendix A.1 for the explicit formulae).[9] If $h_H \leq h < h_H\frac{1}{1-\delta}$, the analogous cutoffs are given by $\overline{z}^M_{non}\frac{1}{1+\lambda}$, $\overline{z}^M_{slow}\frac{1}{1+\lambda}$, $\underline{z}^M_{fast}\frac{1}{1+\lambda}$, and $\overline{z}^M_{fast}\frac{1}{1+\lambda}$.

Households with $h \geq h_H\frac{1}{1-\delta}$ are always non-learners, since their human capital guarantees high-sector employment next period without further investment. For them, only the cutoff $\overline{z}^H_{non}(a)\frac{1}{1+\lambda}$ matters.

[9]Appendix A.2 provides parameter restrictions for $\overline{z}^M_{fast}(a) > \underline{z}^M_{fast}(a)$.

3.2 The Effects of Uninsured Idiosyncratic Risk

We now reintroduce the idiosyncratic risk to households in period 1 by assuming that z' follows a log-normal distribution with mean $\overline{z}'$ and variance σ_z^2.

Our previous analysis without uncertainty is a special case with $\sigma_z^2 = 0$. The effects of uninsured idiosyncratic risk can be thought as how households' decisions change when the distribution of z' undergoes a mean-preserving spread in the sense of second-order stochastic dominance.

From a consumption-saving perspective, the uncertain z' is associated with future labor income risk. It is well understood in the literature that idiosyncratic future income risk raises the expected marginal utility of future consumption for households with log utility and makes them save more. In our model, households can also supply more labor to mitigate the effect of idiosyncratic income risk on the marginal utility of consumption.

From the perspective of human capital investment, the uncertain z' is associated with risk in the return to human capital. Conditional on working, households' income increases with z': $c' = (1 + r')a' + w'x(h')z'$. $\ln(c')$ is increasing and concave in z', and a higher $x(h')$ increases the concavity.[10] Consider two levels of h', $\overline{h'} > \underline{h'}$, a mean-preserving spread of z' distribution reduces the expected utility at both levels of h' but the reduction is larger for the higher level $\overline{h'}$. Hence, the expected utility gain of moving from $\underline{h'}$ to $\overline{h'}$ is smaller due to the idiosyncratic risk. Human capital investment is discouraged.

Taking into account endogenous labor supply reinforces the discouragement of human capital investment by the idiosyncratic risk. Recall from Section 3 that households with z' lower than a cutoff do not work. The endogenous labor supply therefore provides insurance against the lower tail risk of the idiosyncratic z'. Moreover, the cutoff in z' is lower for those with higher human capital h'. This makes households with higher h' more exposed to the lower tail risk than those with lower h', further reducing the gain of human capital investment.

Proposition 1. *The uninsured idiosyncratic risk in z' makes households in period 1 save more, work more and invest less in human capital.*

[10]The marginal effect of z' on $\ln(c')$ is

$$\frac{\partial \ln(c')}{\partial z'} = \frac{w'x(h')}{(1 + r')a' + w'x(h')z'} > 0$$

The second derivative is

$$\frac{\partial^2 \ln(c')}{(\partial z')^2} = -\left[\frac{w'x(h')}{(1 + r')a' + w'x(h')z'}\right]^2 < 0$$

and is more negative if $x(h')$ is higher.

3.3 Period-1 Saving and Human Capital Investment

In this section, we study the impact of endogenous human capital investment on households' saving decisions. Specifically, we compare optimal saving behavior in two scenarios: one in which households can choose to invest in human capital, and an alternative scenario in which human capital is exogenously fixed. To facilitate the comparison, we assume in this section that there is no human capital depreciation.[11]

When the optimal choice of human capital investment is zero, optimal saving is identical in both scenarios. When the optimal human capital investment is either e_L or e_H, we compare the household's optimal saving to the case where human capital investment is exogenously fixed at zero, i.e., $(n = 1, e = 0)$.[12]

To make the human captial relevant, we assume that $n' = 1$ in period 2. The additive separability of work and human capital investment effort from consumption allows us to consider the optimal saving conditional on a given choice of labor supply and human capital investment.

In particular, the household maximizes expected lifetime utility:

$$\max_{a'} : \ln(c) + \beta \mathbb{E}_{z'}[\ln(c')], \tag{24}$$

subject to the budget constraints

$$c + a' = (1 + r)a + n(wzx(h)), \tag{25}$$

$$c' = (1 + r')a' + w'z'x(h'), \tag{26}$$

$$\text{with } h' = ye + (1 - \delta)h, e \in \{0, e_L, (1 - n)e_H\} \tag{27}$$

3.3.1 Effect of on-job-training on saving

We now compare the optimal saving between $(n = 1, e = e_L)$ and $(n = 1, e = 0)$, where e_L allows households to move to a higher sector in period 2 with higher sectoral productivity $x(h')$.

To simplify the notation while maintaining the key economic forces, we normalize $(1 + r) = (1 + r') = 1$, $w = w' = 1$, the period-1 productivity shock $z = 1$, the period-1 learning-ability shock $y = 1$, and the period-2 productivity shock z' to

[11]If depreciation is allowed, the analysis proceeds similarly but involves more comparison paris.

[12]Why not compare to $(n = 0, e = 0)$? Such a comparison is not meaningful when considering $(n = 1, e = e_L)$ because the two scenarios involve different state spaces. To see it, suppose conditions are such that $(n = 1, e = e_L)$ is optimal. If we were to fix $e = 0$ exogenously, the household's lifetime income would fall, and as a result the household would have a greater incentive to work. Thus, it is not possible for the household to deviate from choosing $n = 1$ when human capital is held fixed at $e = 0$. The comparison between $(n = 0, e = 0)$ and $(n = 0, e = e_L$ or $e_H)$ is similar to the comparison between $(n = 1, e = 0)$ to $(n = 1, e = e_L)$, since human capital investment does not affect period-1 labor income in either case.

$\ln z' \sim \mathcal{N}(0, \sigma_z^2)$. The budget constraints become:

$$c + a' = a + x, \quad c' = a' + txz' \tag{28}$$

where x is the household's period-1 labor income that reflects both productivity and skill. $t \geq 1$ represents the effect of human capital investment on period-2 income: $t > 1$ if $e = e_L$; $t = 1$ if $e = 0$.

The optimal saving is determined by the FOC:

$$\frac{1}{a + x - a'} = \beta \mathbb{E}_{z'} \Big(\frac{1}{a' + txz'} \Big) \tag{29}$$

Denoting the mean and variance of z' as μ and Σ, respectively:

$$\mu \equiv \mathbb{E}[z'] = e^{\sigma_z^2/2}, \quad \Sigma \equiv \mathrm{Var}(z') = e^{\sigma_z^2}(e^{\sigma_z^2} - 1). \tag{30}$$

The second-order approximate solution to the FOC is:

$$a'^{*}(x, a; t) = \underbrace{\frac{\beta(a + x) - tx\mu}{1 + \beta}}_{\text{CE}} + \underbrace{\frac{t^2 x^2 \Sigma}{\beta(a + x + tx\mu)}}_{\text{Precautionary}} \tag{31}$$

The first term is the *certainty-equivalent* saving, which reflects the consumption smoothing motive, increasing in the period-1 resources $a + x$ and decreasing in the period-2 expected labor income $tx\mu$. The second term is the *precautionary* saving, which is increasing in the variance of period-2 labor income $t^2x^2\Sigma$ and decreasing in the expected total resources $a + x + tx\mu$.

The effect of on-job-training on saving can be decomposed into two components:

$$\frac{\partial a'^{\star}}{\partial t}(x, a; t) = -\frac{x\mu}{1 + \beta} + \frac{x^2 \Sigma}{\beta} \frac{t\,[2(a + x) + tx\mu]}{(a + x + tx\mu)^2}. \tag{32}$$

The first term being negative captures the *crowd-out* effect on saving via consumption-smoothing motive as on-job-training increases the expected period-2 labor income $tx\mu$. The second positive term captures the *crowd-in* effect via precautionary saving motive as on-job-training exposes households to larger future income risk.

To capture the overall impact of on-job-training on saving, we define:

$$\Delta_{\text{on-job}}(x, a; t) = a'^{\star}(x, a; t) - a'^{\star}(x, a; 1) = \int_1^t \frac{\partial a'^{\star}}{\partial u}(x, a; u) du, \tag{33}$$

where $a'^{\star}(x, a; t)$ is the optimal saving when households undertake on-job-training, and $a'^{\star}(x, a; 1)$ is the optimal saving when human capital is kept exogenously fixed.

Whether on-job-training increases or decreases saving ultimately depends on the balance between the crowd-out effect (via higher expected future income) and the precautionary crowd-in effect (via heightened future income risk). The next proposition demonstrates that these effects can dominate differently depending on period-1 income x, so that the overall impact of on-job-training on saving can differ between low- and high-income households.

Proposition 2. *If the idiosyncratic risk is large enough, i.e., $\frac{\Sigma}{\mu} > \sigma^*(t)$, on-job-training crowds out saving for low-income households and crowds in saving for high-income households: for $x < x^*(a,t)$, $e = e_L$ lowers saving $\Delta_{\text{on-job}}(x,a;t) < 0$; for $x > x^*(a,t)$, $e = e_L$ raises saving $\Delta_{\text{on-job}}(x,a;t) > 0$.*

Proof. See Appendix B. □

3.3.2 Effect of full-time training on saving

We next compare the optimal saving between $(n = 0, e = e_L \text{ or } e_H)$ and $(n = 1, e = 0)$. Note that full-time training requires the households to give up their labor income in period 1, which is not the case for on-job-training. Following the same normalization and notation as in the previous subsection, we can write the budget constraints with full-time training and without training as:

$$e = e_H: \quad c + a' = a, \quad c' = a' + txz' \tag{34}$$

$$e = 0: \quad c + a' = a + x, \quad c' = a' + xz' \tag{35}$$

where $t > 1$ captures the effect of full-time training on period-2 income.

The second-order approximation to the optimal saving problem yields:

$$e = e_H: \quad a'^*_{e_H}(x,a;t) = \underbrace{\frac{\beta a - tx\mu}{1+\beta}}_{\text{CE}} + \underbrace{\frac{t^2x^2\Sigma}{\beta(a+tx\mu)}}_{\text{Precautionary}} \tag{36}$$

$$e = 0: \quad a'^*(x,a;1) = \underbrace{\frac{\beta(a+x) - x\mu}{1+\beta}}_{\text{CE}} + \underbrace{\frac{x^2\Sigma}{\beta(a+x+x\mu)}}_{\text{Precautionary}} \tag{37}$$

The overall effect of full-time training on saving can be expressed as:

$$\begin{aligned}\Delta_{\text{full-time}}(x,a;t) &= a'^*_{e_H}(x,a;t) - a'^*(x,a;1) \\ &= \Delta_{\text{on-job}}(x,a;t) + \Delta_H(x,a;t)\end{aligned} \tag{38}$$

$$\text{where } \Delta_H(x,a;t) \equiv x\left[-\frac{\beta}{1+\beta} + \frac{\Sigma}{\beta}\frac{t^2x^2}{(a+x+tx\mu)(a+tx\mu)}\right] \tag{39}$$

Here, $\Delta_H(x,a;t)$ captures the additional impact of full-time training on saving, over and above that of on-job-training. The first term reflects a further reduction in saving due to the need to forgo period-1 labor income. The second term shows an increase in precautionary saving, as reduced current resources limit households' ability to self-insure against idiosyncratic risk in period 2.

The following lemma establishes some properties of $\Delta_H(x, a; t)$:

Lemma 1. *If $\frac{\Sigma}{\mu} < \hat{\sigma}(t)$, $\Delta_H(x, a; t) < 0$ and decreases in x. If $\frac{\Sigma}{\mu} > \overline{\sigma}(t)$, $\Delta_H(x, a; t) > 0$ if and only if $x > \hat{x}(a, t)$; moreover, for $x > \hat{x}(a, t)$, $\Delta_H(x, a; t)$ increases in x.*

Proof. See Appendix B. □

Taken together, Proposition 2 and Lemma 1 imply that, when the idiosyncratic risk is large enough, full-time training *crowds out* saving for low-income households, but *crowds in* saving for high-income households.

Proposition 3. *If the idiosyncratic risk is large enough, i.e., $\frac{\Sigma}{\mu} > \max\{\sigma^*(t), \hat{\sigma}(t)\}$, full-time training crowds out saving for low-income households and crowds in saving for high-income households: for $x < \min\{x^*(a, t), \hat{x}(a, t)\}$, $e = e_H$ lowers saving $\Delta_{\text{full-time}}(x, a; t) < 0$; for $x > \max\{x^*(a, t), \hat{x}(a, t)\}$, $e = e_H$ raises saving $\Delta_{\text{full-time}}(x, a; t) > 0$.*

3.4 The Effects of an Anticipated Period-2 AI Shock

Suppose that an AI shock is anticipated to occur in period 2 and to increase the labor productivity for the low sector and the high sector but not the middle sector. The effect of AI shock on the sectoral productivity is captured by γ with $0 < \gamma < 1$:

$$x(h') = \begin{cases} 1 - \lambda + \gamma\lambda & \text{low sector if } h' < h_M \\ 1 & \text{middle sector if } h_M < h' < h_H \\ 1 + \lambda + \gamma\lambda & \text{high sector if } h' > h_H \end{cases} \tag{40}$$

In other words, the AI shock increases average labor productivity, reduces the earnings premium for the middle sector, and enlarges the earnings premium for the high sector relative to the middle sector.

3.4.1 Effects on human capital investment

The AI shock lowers the incentive to work in the middle sector in period 2. Consequently, households with $h < h_M/(1-\delta)$ reduce their human capital investment, while those with $h > h_M/(1-\delta)$ increase it. More specifically, the upper bounds that determine whether households undertake positive human capital investment – denoted by $\overline{z}^L_{slow}$ and $\overline{z}^L_{fast}$ for $h < h_M/(1-\delta)$, and $\overline{z}^M_{slow}$ and $\overline{z}^M_{fast}$ for $h > h_M/(1-\delta)$ – respond in opposite directions to the anticipated shock: the former decrease with γ and the latter increase. This relationship is formalized below.

Proposition 4. *An anticipated AI shock decreases human capital investment among households with $h < h_M/(1-\delta)$, but increases it among those with $h > h_M/(1-\delta)$. Specifically, $\overline{z}^L_{slow}$ and $\overline{z}^L_{fast}$ decrease with γ, while $\overline{z}^M_{slow}$ and $\overline{z}^M_{fast}$ increase with γ.*

Proof. See Appendix B. □

3.4.2 Effects on labor supply

via income: The AI shock raises period-2 labor income for households who will work in the low or high sector, leading to a positive income effect that reduces their labor supply in period 1.

via full-time training: Because full-time training and labor supply compete for time, the AI shock affects their tradeoff through its impact on human capital investment incentives. For $h > h_M/(1-\delta)$, where AI makes investing in additional skills more attractive, households are more likely to engage in full-time training and thus reduce period-1 labor supply. In contrast, for $h < h_M/(1-\delta)$, where the AI shock lowers the payoff to investing in skills, households shift away from full-time training and supply more labor in the first period.

3.4.3 Effects on saving

The AI shock increases sectoral labor productivity for the low and high sectors in period 2, while leaving the middle sector's labor productivity unchanged. Its effect on saving can be analyzed as if we are varying the parameter t in the functions $\Delta_{\text{on-job}}(x, a; t)$, defined in (33), and $\Delta_H(x, a; t)$, defined in (39).

Proposition 5. *$\Delta_H(x, a; t)$ is increasing in t. $\Delta_{\text{on-job}}(x, a; t)$ is convex in t:*

- *If $\Delta_{\text{on-job}}(x, a; t) > 0$ and $t > 1$, $\Delta_{\text{on-job}}(x, a; t') > \Delta_{\text{on-job}}(x, a; t)$ for $t' > t > 1$.*
- *If $\Delta_{\text{on-job}}(x, a; t) > 0$ and $t < 1$, $\Delta_{\text{on-job}}(x, a; t') < \Delta_{\text{on-job}}(x, a; t)$ for $1 > t' > t$.*

Proof. See Appendix B. □

Households who stay in the same sector For middle-sector households, the AI shock leaves both their incomes and saving unchanged.

By contrast, low-sector and high-sector households experience an increase in period-2 labor income x' as a result of the AI shock. If they remain in the same sector without needing additional human capital investment or on-the-job training, their saving behavior in the absence of the AI shock can be compared to the scenario with fixed human capital. Following the AI shock, however, their situation resembles one with on-the-job training that enhances x' (i.e., $t > 1$). Thus, the effect of the AI shock on saving is captured by the on-the-job training impact, $\Delta_{\text{on-job}}(x, a; t)$.

As shown in Proposition 2, $\Delta_{\text{on-job}}(x, a; t)$ has opposite signs for low-skill and high-skill households. This implies that the AI shock *crowds out* saving among low-sector households, while it *crowds in* saving for high-sector households.

For households who must undertake full-time training to remain in the high sector, $\Delta_H(x, a; t)$ captures the additional effect of such training on saving. In this case, a higher x'—brought about by the AI shock—corresponds to an increase in t, further boosting $\Delta_H(x, a; t)$ (Proposition 5). Consequently, the AI shock *crowds in* saving for high-sector households in this scenario as well.

Households who upskill For low-sector households, saving behavior remains unchanged, as the AI shock does not affect their future productivity after upskilling.

For the middle-sector households who upskill via on-job-training, the AI shock boosts their future productivity gain from λ to $(1 + \gamma)\lambda$, which corresponds to a higher t in $\Delta_{\text{on-job}}(x, a; t)$ with $t > 1$. According to Proposition 5, if the pre-shock effect of on-the-job training on saving is positive, the AI shock will *raise* saving. However, if this effect is negative, the overall impact of the AI shock on saving becomes ambiguous.

For the middle-sector households who upskill via full-time training, there is an *additional positive effect* of the AI shock on their saving, because a higher x' increases $\Delta_H(x, a; t)$ (Proposition 5).

Households who downskill Downskilling, which reflects human capital depreciation, does not require any new investment in skills. For high-sector households who transition downward, the AI shock leaves their future productivity – and thus their saving – unchanged.

For middle-sector households who downskill to the low sector, their saving differs from the fixed human capital scenario by $\Delta_{\text{on-job}}(x, a; t)$ with $t < 1$. The AI shock mitigates their future productivity loss by reducing it from λ to $(1-\gamma)\lambda$, effectively increasing t to a new value $t' < 1$. According to Proposition 5, if the pre-shock effect $\Delta_{\text{on-job}}(x, a; t)$ is positive, the AI shock will *reduce* saving. If this effect is negative, however, the overall impact of the AI shock on saving is ambiguous.

3.5 Limitations of the two-period model

Up to this point, our analysis has focused on how AI influences household-level decisions regarding human capital investment, labor supply, and saving within the framework of a two-period model. While this provides valuable insights into individual behavioral responses, understanding the broader, economy-wide implications of AI requires moving to a more comprehensive setting – a quantitative model with an infinite time horizon, endogenous asset accumulation, and general equilibrium feedback.

General equilibrium (GE) effects When households adjust their investment in human capital, labor supply, and savings in response to AI, these changes aggregate up to affect the total supply of effective labor and capital in the economy. As these aggregates shift, they exert downward or upward pressure on the wage rate and the interest rate, feeding back into each household's optimization problem. Thus, general equilibrium effects capture the intricate loop by which individual decisions shape, and are shaped by, the macroeconomic environment.

Composition effects Endogenizing human capital investment injects dynamism into how households sort themselves among the three skill sectors. When an AI shock occurs, individuals may choose to retrain, upskill, or even move to lower-skilled work, reshaping the distribution of labor across sectors. This shifting composition changes the relative size of each sector, with significant consequences for both aggregate outcomes and the distributional effects of AI.

4 A Quantitative Model

We now solve the full dynamic model with infinite horizon, endogenous asset accumulation, and general equilibrium. We calibrate the model to reflect key features of the U.S. economy, capturing reasonable household heterogeneity.

4.1 Calibration

We calibrate the model to match the U.S. economy. For several preference parameters, we adopt values commonly used in the literature. Other parameters are calibrated to align with targeted moments. The model operates on an annual time period. Table I summarizes the parameter values used in the benchmark model.

The time discount factor, β, is calibrated to match an annual interest rate of 4 percent. We set χ_n to replicate an 80 percent employment rate. We calibrate χ_e to match the fact that around 30 percent of the population invests in human capital (**oecd2025adultlearning**).

We calibrate parameters regarding labor productivity process as follows. We assume that z follows the AR(1) process in logs: $\log z' = \rho_z \log z + \epsilon_z$, where $\epsilon_z \sim N(0, \sigma_z^2)$. The shock process is discretized using the **tauchen1986finite** method, resulting in a transition probability matrix with 11 grids. We set the persistence parameter to $\rho_z = 0.948$ and the standard deviation to $\sigma_z = 0.269$, following the estimates reported in Chang and Kim (2006).

We deviate from the two-period model by assuming that the labor supply is a discrete choice between 0 and $\overline{n} = 1/3$. This change only rescales the two-period model without altering the trade-off facing the households. But such rescaling facilitates the interpretation that households are deciding whether to allocate one-third of their fixed time endowment to work. The high-level human capital accumulation effort, e_H is assumed to equal $\overline{n}$. The low-level effort, e_L is set to half of e_H. The skill

Table I: Parameters for the Calibration

Parameter	Value	Description	Target or Reference
β	0.91795	Time discount factor	Annual interest rate
ρ_z	0.948	Persistence of z shocks	Chang and Kim (2006)
σ_z	0.269	Standard deviation of z shocks	Chang and Kim (2006)
$\underline{a}$	0	Borrowing limit	See text
χ_n	2.47	Disutility from working	Employment rate
χ_e	1.48	Disutility from HC effort	See text
$\overline{n}$	1/3	Hours worked	Average hours worked
e_H	1/3	High level of effort	Average hours worked
e_L	1/6	Low level of effort	See text
h_M	0.41	Human capital cutoff for M	See text
h_H	0.96	Human capital cutoff for H	See text
λ	0.2	Skill premium	Earnings Gini
δ_h	0.1	HC depreciation rate	Standard value
α	0.36	Capital income share	Standard value
δ	0.1	Capital depreciation rate	Standard value

premium across sectors, λ, is set at 0.2 to match the earnings Gini coefficient. Human capital cutoffs, h_M and h_H, are set so that the population shares in low, middle, and high sectors are, respectively, 20, 40, and 40 percent. This population distribution roughly matches the fractions of U.S. workers in 2014 who are employed in routine manual occupations (low sector), routine cognitive and non-routine manual (middle sector), and non-routine cognitive (high sector) (Cortes *et al.*, 2017).

On the production side, we set the capital income share, α, to 0.36, and the depreciation rate, δ, to 0.1. For simplicity, we assume that human capital depreciates at the same rate, i.e., $\delta_h = 0.1$.

4.2 Key Moments: Data vs. Model

In Table II, we present a comparison of key moments between the model and the empirical data. The model does an excellent job of replicating the 80% employment rate observed in the data. In this context, employment is defined as having positive labor income in the given year, consistent with the common approach used in the literature. According to **oecd2025adultlearning**, the share of the population investing in human capital—those who are actively engaged in skill acquisition or education—is approximately 30%, a figure well matched by the model's predictions. This is an important metric because it reflects the model's capacity to capture the dynamics of human capital formation, which plays a critical role in shaping long-run earnings and income inequality. Additionally, the model accurately captures the distribution of income and earnings, aligning closely with observed data. This suggests that the model effectively incorporates the key mechanisms driving labor market

Table II: Key Moments

Moment	Data	Model
Employment rate	0.80	0.80
Human capital investment ratio	0.29	0.29
Gini coefficient for wealth	0.78	0.76
Gini coefficient for earnings	0.63	0.62
Gini coefficient for income	0.57	0.58

outcomes and the corresponding distributional aspects of earnings. Although the model does not explicitly target the wealth Gini coefficient, it achieves a close match to the data: the empirical wealth Gini is 0.78, while the model produces a value of 0.76. This highlights the model's ability to capture substantial wealth inequality in the economy.

4.3 Steady-state Distribution

Table III presents the steady-state distribution of population, employment, and assets across sectors. The population shares are calibrated to 20%, 40%, and 40% by adjusting the human capital thresholds that define sectors. The shares of employment and assets are endogenously determined by households' labor supply and savings decisions. Notably, the high sector accounts for 46% of total employment—exceeding its population share—indicating that a disproportionate number of households choose to work in that sector. Asset holdings are even more skewed: the high sector holds 68% of total assets, while the low sector holds only 8%.

Table III: Distribution of Population, Employment and Assets

Sectors	Pop. Share (%)	Emp. Share (%)	Assets Share (%)
Low	20.76	18.58	8.07
Middle	38.87	35.35	23.92
High	40.35	46.07	68.01

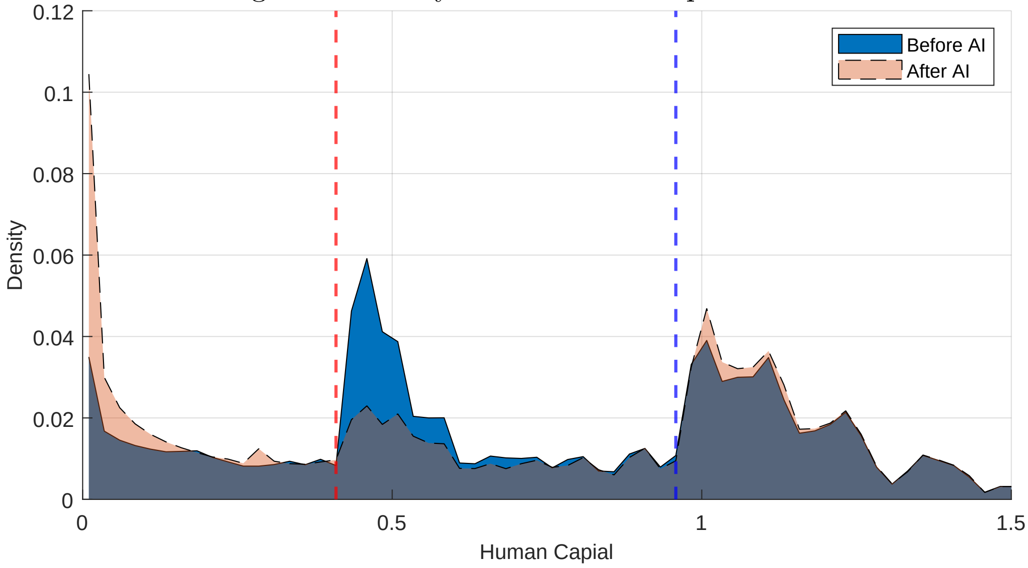
Note: Human capital cutoffs, h_H and h_M, determine the population share across sectors. Employment share and assets share are implied by households labor supply decisions and saving decisions.

5 AI's Impact on Human Capital Adjustments

We now introduce AI technology into the quantitative model, assuming that it will be implemented in 10 years and that households have full information about its arrival. We examine both the transition dynamics and the differences between the initial and new steady states. This framework allows us to analyze how the economy adjusts in anticipation of, and in response to, the adoption of AI.

The effect of AI on the sectorial productivity is modeled as in (40) with $\gamma = 0.3$. That is, AI boosted the productivity of the low sector workers by 7.5% and the productivity of the high sector workers by 5%, leaving the middle sector intact.

Figure 3: Steady-state Human Capital Distribution



Note: The x-axis denotes the level of human capital, while the y-axis indicates the mass of households at each human capital level. The red vertical line marks the cutoff between the low and middle sectors, and the blue vertical line marks the cutoff between the middle and high sectors.

It captures the key idea that AI increases average labor productivity (Acemoglu and Restrepo, 2019), but reduces the earning premium for the middle sector, and enlarges the earning premium for the higher sector relative the middle sector.

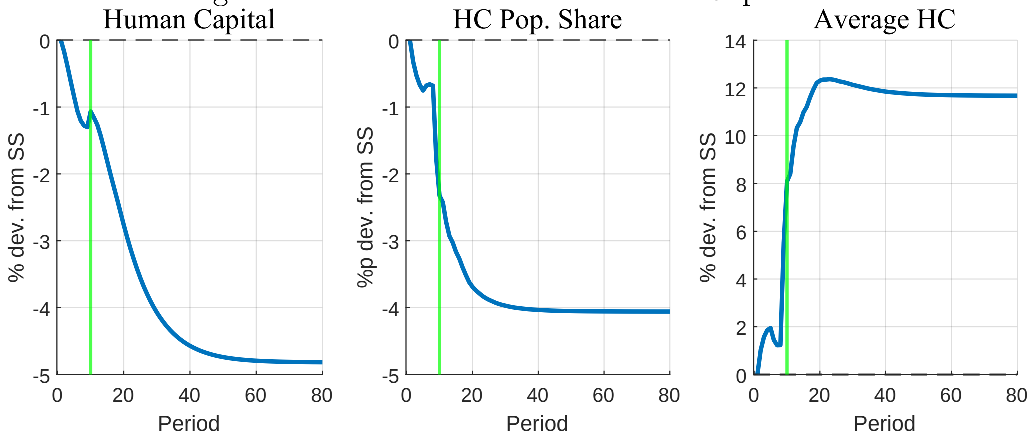
5.1 Human Capital Adjustments

Given the employment distribution in the initial steady state, AI is projected to increase the economy's labor productivity by 4% on average, assuming households do not alter their decisions in response. However, changes in earning premiums incentivize households to adjust their human capital investments.

Steady-state human capital distribution: Figure 3 illustrates how households reallocate across sectors in the new steady state relative to the initial one. The x-axis denotes the level of human capital, while the y-axis indicates the mass of households at each human capital level. The red vertical line marks the cutoff between the low and middle sectors, and the blue vertical line marks the cutoff between the middle and high sectors.

The gray shaded area shows the overlap between the two steady-state distributions. Within each sector, the distribution of households is skewed to the left, reflecting the tendency for human capital investment to be concentrated among those near the sectoral cutoffs. As shown in the decision rule diagram in Figure 2, some households seek to upgrade their skills, while others aim to remain in more skilled sectors. The blue shaded area highlights the mass of households who have exited the middle sector following the AI shock. The pink areas represent the additional mass of households in the new steady-state distribution, concentrated at the

Figure 4: Transition Path for Human Capital Investment



Note: The x-axis represents years, and the y-axis shows the percentage (or percentage point) deviation from the initial steady state. AI introduction is assumed to occur in period 10. "HC Pop. Share" denotes the fraction of households that make positive human capital investments, and "Average HC" denotes average human capital among those investing households.

lower end of the low sector and the lower end of the high sector.

Transition path Figure 4 reports the transition dynamics of aggregate human capital from the initial to the new steady state. The figure also displays its extensive margin (the share of households making positive human capital investments) and intensive margin (average human capital per household among those who invest).

As households reallocate from the middle sector to the low and high sectors, the net effect is a gradual decline in aggregate human capital along the transition path. This mirrors the steady-state change observed in Figure 3, where the increased mass at the lower end of the low sector outweighs the increase in the high sector.

Additionally, human capital accumulation becomes increasingly concentrated among a smaller share of the population. The proportion of households making positive human capital investments steadily declines, ultimately stabilizing at a level 4% lower than in the initial steady state. Meanwhile, the average human capital among those who invest rises, reaching a level 12% higher than the initial steady state in the long run.[13]

5.2 Job Polarization

An important implication of human capital adjustments to the AI shock is job polarization. Figure 5 illustrate the transition paths of population shares and employment rates in each sector. Notably, the middle sector experiences a significant decline, with its population share decreasing by approximately 13%. Additionally, employment within this sector plummets to a level 16% lower than the initial steady state. In contrast, both the low and high sectors see increases in their population

[13]The only exception to those patterns occurs at period 10 when the positive effects of AI on sectoral productivity are realized.

shares and employment rates. These dynamics indicate a reallocation of *workers* from the middle sector to the low and high sectors following the introduction of AI.

Voluntary job polarization This worker reallocation aligns with the phenomenon of "job polarization" (Goos *et al.*, 2014), where AI and automation technologies disproportionately replace tasks commonly performed by middle-skilled workers. However, our model introduces a complementary mechanism to the conventional understanding of this reallocation. Specifically, households in our model voluntarily exit the middle sector even before AI implementation by adjusting their human capital investments – many middle-sector workers opt for non-employment to invest in skills that will better position them for the post-AI labor market.[14] This mechanism is formally characterized in Proposition (4) in the two period model above.

Employment flows more towards the low sector Another intriguing finding in our model is the more pronounced employment effect in the low sector compared to the high sector. In the new steady state, the employment rate in the low sector increases by 12%, whereas in the high sector, it rises by only 0.5%. This asymmetry in employment rate changes suggests an unbalanced reallocation of workers from the middle sector, with a greater flow toward the low sector.

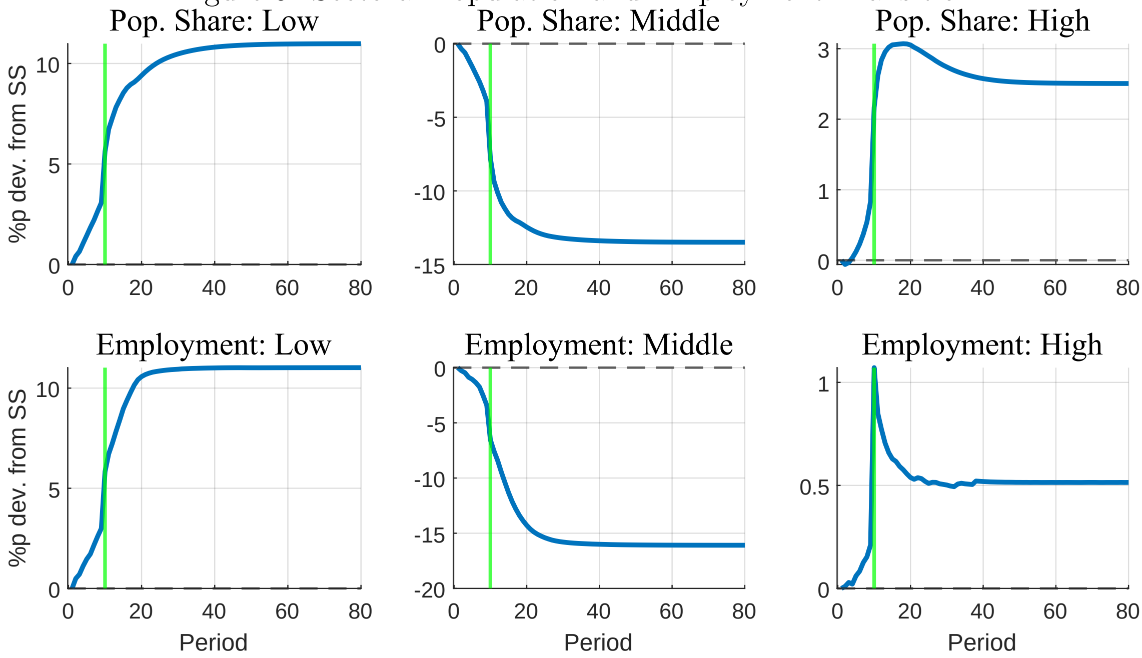
This disparity arises from two key factors. First, AI enhances the productivity of low-sector workers by 7.5% and high-sector workers by 5%. However, this productivity differential alone does not fully account for the significant asymmetry. The second factor is the variation in labor supply elasticity across sectors. Compared to the high sector, the low sector exhibits higher labor supply elasticity, meaning that the same change in labor earnings triggers larger labor supply responses. This is because households in the low sector have lower consumption levels, making their marginal utility of consumption more sensitive to changes in their budget. Consequently, a greater proportion of households in the low sector are at the margin between employment and non-employment (Chang and Kim, 2006).

6 The Aggregate and Distributional Effects of AI

The aggregate and distributional effects of AI are shaped by both its direct impact on sectoral productivity and the endogenous response of human capital accumulation. By altering sectoral productivity, AI changes labor earnings, which in turn influences labor supply decisions and savings through income effects. Consequently, AI directly affects the supply of labor and capital, generating aggregate economic responses. Because AI's productivity effects are heterogeneous across sectors, its impact is inherently distributional.

[14] To emphasize this key difference, our model deliberately abstracts from any direct negative effect of AI on middle-sector workers.

Figure 5: Sectoral Population and Employment Transition



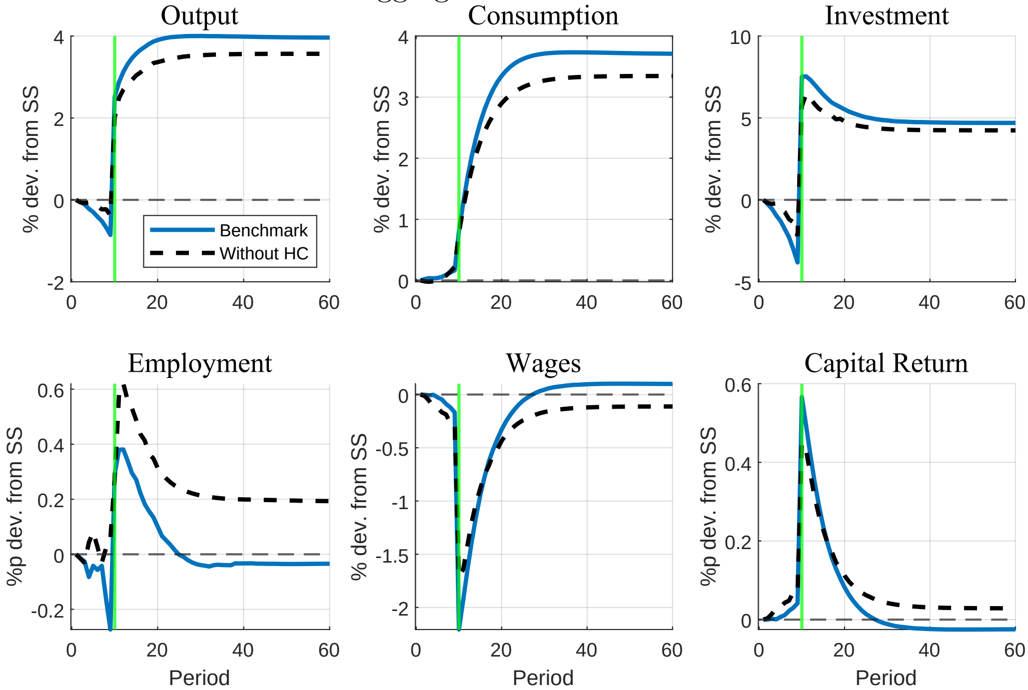
Note: The transition paths within each sector. The x-axis represents years, and the y-axis shows the percentage (or percentage point) deviation from the initial steady state. AI introduction is assumed to occur in period 10. “Pop. Share” denotes the population share within each sector. “Employment” is the percentage of households who are employed in each sector.

These sectoral differences also induce human capital adjustments, as households reallocate across sectors in response to changing incentives. This reallocation not only shifts the distribution of labor productivity and aggregate productivity, but also directly shapes distributional outcomes, as households’ relative positions in the income and asset distributions are altered by their movement across sectors.

In this section, we examine the importance of endogenous human capital adjustment in shaping both the transitional and long-run effects of AI. To do so, we compare the benchmark economy – where households endogenously adjust their human capital – with an alternative scenario in which households are held fixed at their initial steady-state human capital during the AI transition (“No HC model”). In both cases, households make endogenous decisions about consumption, savings, and labor supply.

By contrasting the transition dynamics across these two economies, we can disentangle the direct and indirect effects of AI. The transition path in the No-HC-model isolates the direct impact of AI on aggregate and distributional outcomes, as it abstracts from any human capital adjustments. The difference in outcomes between the benchmark and the No-HC-model then reveals the indirect effects of AI that operate through households’ adjustments in human capital. This decomposition allows us to assess the relative importance of human capital dynamics in driving both the aggregate and distributional consequences of AI.

Figure 6: Transition Path of Aggregate Variables: Benchmark vs. No HC Models.



Note: The transition paths of aggregate variables: benchmark vs. No HC models. The x-axis represents years, and the y-axis shows the percentage deviation from the initial steady state. AI introduction is assumed to occur in period 10. The No HC model is an economy in which workers maintain their initial steady-state level of human capital throughout the AI implementation until the new steady state is reached.

6.1 Aggregate Implications

Figure 6 shows the transition paths of key macroeconomic variables—output, consumption, investment, and employment—as well as factor prices, including the wage rate and capital return. The blue solid lines depict results from the benchmark model with endogenous human capital adjustment, while the black dashed lines represent the No-HC model in which human capital is held fixed.

6.1.1 AI's direct impacts

The No-HC-model isolates the direct effects of AI. In the long run, the introduction of AI leads to higher output, consumption, investment, and employment. However, in anticipation of AI (prior to period 10), output and investment decline, while consumption and employment remain stable.

Before the implementation of AI, sectoral productivity is unchanged; the only difference is households' awareness of future increases in productivity in the low and high sectors beginning in period 10. This anticipation raises households' expected lifetime income, prompting them to save less and consume more ahead of the actual productivity gains. As a result, aggregate capital stock falls, which lowers output and reduces the marginal product of labor while raising the marginal product of capital. Employment remains largely unchanged in this period, as sectoral productivity has not yet shifted.

Following the AI shock, sectoral productivity in the low and high sectors rises, boosting labor income, employment, and output in these sectors. Because productivity gains are labor-augmenting, the supply of efficient labor units rises sharply, causing wages to decline and capital returns to increase. Employment and investment both adjust to dampen these factor price changes. In the new steady state, the wage rate is slightly below its initial level, while the return to capital is marginally higher.

6.1.2 AI's indirect impacts via endogenous human capital adjustments

The difference between the No-HC model and the benchmark model captures the indirect effects of AI operating through endogenous human capital adjustments. Among all macroeconomic variables, this indirect effect is most pronounced for employment.

In anticipation of AI, employment declines as some households temporarily exit the labor market to invest in human capital and prepare for the post-AI economy.[15] During this period, labor productivity remains unchanged, so the decline in employment directly translates to a reduction in output. Consistent with standard consumption-smoothing behavior, this reduction is mainly absorbed by lower investment. Meanwhile, the drop in employment mitigates the direct effects of AI on both wages and capital returns prior to the AI implementation.

After AI is introduced, employment rebounds as sectoral productivity increases. However, continued human capital investment by middle-sector households keeps employment lower than in the No-HC model, resulting in an almost neutral long-run effect of AI on employment. Despite this, output, consumption, and investment are all higher in the benchmark model because human capital adjustments reallocate more labor to the low and high sectors, thereby better capturing the productivity gains from AI.

This reallocation also reverses the steady-state comparison of factor prices: endogenous human capital adjustment transforms the negative direct effect of AI on the wage rate into a positive net effect, and the positive direct effect on capital returns into a negative net effect.

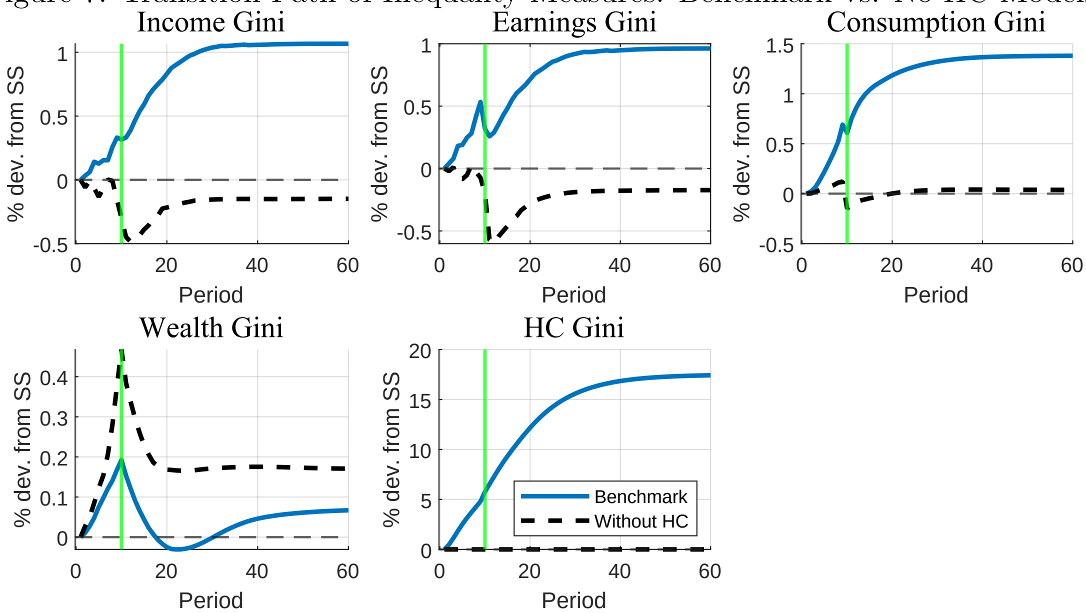
6.2 Distributional Implications

The findings above underscore the importance of accounting for human capital adjustments when assessing the aggregate impact of AI, as households actively adapt to a rapidly evolving labor market. When it comes to economic inequality, endogenously adjusting human capital plays an even more significant role.

Figure 7 shows the transition paths of Gini coefficients for earnings (labor income), total income (capital and labor income), consumption, wealth (asset hold-

[15] Empirical studies, such as Lerch (2021) and Faber *et al.*, (2022), support the short-term adverse effects of AI adoption on labor markets.

Figure 7: Transition Path of Inequality Measures: Benchmark vs. No HC Models.



Note: The transition paths of inequality measures: benchmark vs. No HC models. The x-axis represents years, and the y-axis shows the percentage deviation from the initial steady state. AI introduction is assumed to occur in period 10. The No HC model is an economy in which workers maintain their initial steady-state level of human capital throughout the AI implementation until the new steady state is reached.

ings), and human capital. The black dashed lines represent results from the No-HC model, capturing the direct impact of AI without human capital adjustment. In contrast, the blue solid lines reflect the benchmark model, where human capital responds endogenously to both anticipated and realized changes in the skill premium induced by AI.

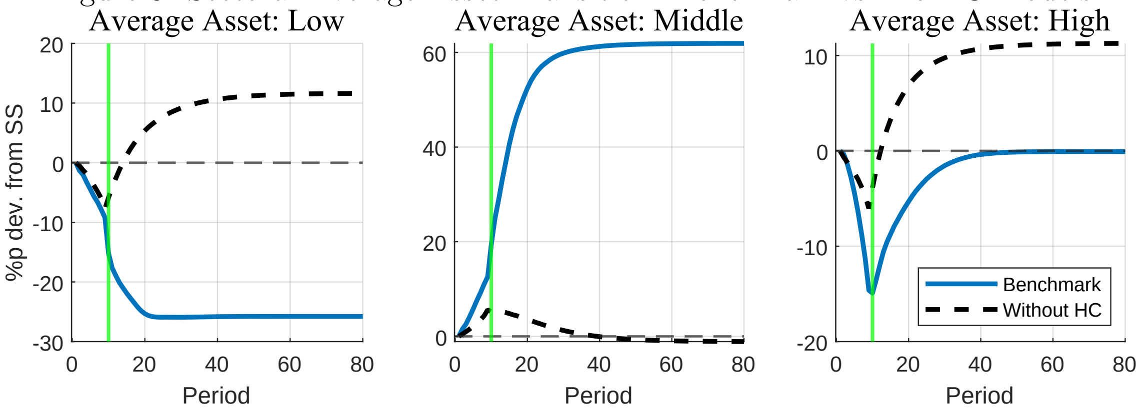
6.2.1 Income, earnings, and consumption inequalities

The comparison of transition paths between the No-HC model and the benchmark model reveals that endogenous human capital adjustments fundamentally alter the impact of AI on income, earnings, and consumption inequalities.

AI's direct impacts: Without any human capital adjustments, AI's impact on inequalities is primarily driven by productivity gains in the low and high sectors – 7.5% and 5%, respectively. As a result, there is little direct impact on income and earnings Gini coefficients in anticipation of AI before period 10. After AI is implemented, both income and earnings inequality decline: higher labor productivity raises earnings in the low sector, while wage declines in the middle sector compress the distribution. Consumption inequality remains largely unchanged throughout the transition.

Effects of AI-induced human capital adjustments: Allowing human capital to adjust endogenously, however, leads to pronounced job polarization, as shown in Section 5.2. Households who would have qualified for middle-sector jobs now tran-

Figure 8: Sectoral Average Asset Transition: Benchmark vs. No HC Models



Note: The transition paths within each sector. "Average Asset" is defined as the total assets in a given sector divided by that sector's population share. The x-axis represents years, and the y-axis shows the percentage (or percentage point) deviation from the initial steady state. AI introduction is assumed to occur in period 10. The No HC model is an economy in which workers maintain their initial steady-state level of human capital throughout the AI implementation until the new steady state is reached.

sition to either the low or high sector. Those moving to the low sector see reduced labor earnings, while those shifting to the high sector enjoy increased earnings. This polarization drives up earnings and income inequality, both before and after AI is implemented. As income disparities widen, consumption inequality also increases.

6.2.2 Wealth inequality

In stark contrast to the effects on income and earnings inequality, allowing for endogenous human capital adjustment mitigates the negative direct impact of AI on wealth inequality. While AI's direct effect would otherwise widen disparities, human capital responses help dampen the increase in wealth inequality, underscoring the stabilizing role of human capital adjustments in the wealth distribution.

As discussed in Section 3.3, the effect of human capital investment on saving is theoretically ambiguous ex ante. On the one hand, higher expected future income from on-the-job and full-time training tends to crowd out saving through the standard consumption-smoothing motive. On the other hand, greater exposure to idiosyncratic risk strengthens the precautionary saving motive and can crowd in saving. Propositions 2 and 3 demonstrate that, when idiosyncratic risk is sufficiently large, human capital investment crowds out saving for low-labor-income households but crowds in saving for high-labor-income households. As labor income is positively affected by households productivity, the net effect of human capital investment on saving is positive precisely for the more productive households.

In our quantitative model, this mechanism shows up most clearly in the middle sector. Figure 8 plots the transition of average assets by sector in the benchmark economy and in the counterfactual No HC economy. "Average Asset" is defined as total assets held by households in a given sector divided by that sector's population share, so it reflects both within-sector saving behavior and the composition of households across sectors.

AI's direct impacts: Without any human capital adjustment, AI's impact on households' saving works purely through income effect. In both the low and high sectors, households reduce their savings in anticipation of AI, expecting higher lifetime labor income. After AI is implemented at period 10, their savings increase alongside rising labor incomes. In contrast, households in the middle sector, anticipating a negative income effect from AI due to a lower wage rate, increase their savings prior to period 10. Once AI is introduced and the wage rate recovers, middle-sector households reduce their savings.

Effects of AI-induced human capital adjustments: Endogenous human capital responses introduce an additional channel. Relative to the No-HC model, the benchmark exhibits a pronounced increase in average assets in the middle sector.[16] Middle-sector households are relatively productive in our model, and a composition effect further amplifies their asset accumulation: many less productive middle-sector households endogenously move down to the low sector, so the remaining middle-sector population is positively selected on productivity.[17] In addition, as discussed above, some middle-sector households voluntarily exit employment to invest in human capital full-time. Taken together, these households are the "active training" and relatively high-productivity workers in our model; thus, as predicted by Propositions 2 and 3, their human capital investment tends to crowd in saving. Accordingly, AI-induced human capital adjustment strengthens asset accumulation in the middle of the distribution and compresses the gap between the middle and the top. Quantitatively, the increase in wealth inequality in the benchmark economy with endogenous human capital is therefore markedly smaller than in the No HC economy, highlighting the stabilizing role of human capital adjustment in the wealth distribution.

7 Conclusion

Recent studies on AI suggest that advancements are likely to reduce demand for junior-level positions in high-skill industries while increasing the need for roles focused on advanced decision-making and AI oversight. We demonstrate how human capital investments are expected to adapt in response to these shifts in skill demand, highlighting the importance of accounting for these human capital responses when assessing AI's economic impact.

[16] In the benchmark model, average assets in the high sector decline due to a composition effect, as relatively low-wealth households move up from the middle sector. In the low sector, average assets also fall, primarily because the scope for precautionary saving is limited, and this effect is reinforced by composition changes.

[17] Note that the share of households moving up is relatively small.

Our work points to several promising directions for future research on the economic impacts of AI. First, if governments implement redistribution policies to address AI-induced inequality, understanding how these policies influence human capital accumulation, and thus their effectiveness, would be valuable. Second, our model assumes households have perfect foresight when making human capital investments. Relaxing this assumption could reveal new insights into the economic trajectory of AI advancements and offer important policy implications.

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A Household Decision Rule Cutoffs

A.1 Additional cutoffs formulae for households

$$\overline{z}^M_{non}(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'}{1+r'}]}{w} \tag{A.1}$$

$$\overline{z}^M_{slow}(a) := \frac{(\exp(\frac{\chi_n - \chi_e e_H}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}] + \lambda\frac{w'z'}{1+r'}}{w} \tag{A.2}$$

$$\underline{z}^M_{fast}(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}]}{w} \tag{A.3}$$

$$\overline{z}^M_{fast}(a) := \frac{\left\{\lambda\left[\exp(\frac{\chi_e e_L}{1+\beta}) - 1\right]^{-1} - 1\right\}\frac{w'z'}{1+r'} - (1+r)a}{w} \tag{A.4}$$

$$\overline{z}^H_{non}(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}]}{w} \tag{A.5}$$

A.2 Parameter restrictions for cutoffs ranking

To guarantee that $(n = 0, e = e_H)$ dominates $(n = 0, e = 0)$, we need a lower bound for λ. The slow learners prefer $(n = 0, e = e_H)$ if and only if

$$(1+\beta)\ln c(n = 0, e = e_H) - \chi_e e_H \geq (1+\beta)\ln c(n = 0, e = 0)$$

or equivalently:

$$\lambda \geq \underline{\lambda}_1 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}}\left(1 - \frac{1}{\exp(\frac{\chi_e e_H}{1+\beta})}\right) \text{ if } h < h_M\frac{1}{1-\delta} \tag{A.6}$$

$$\lambda \geq \underline{\lambda}_3 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}}\left(\exp(\frac{\chi_e e_H}{1+\beta}) - 1\right) \text{ if } h \geq h_M\frac{1}{1-\delta} \tag{A.7}$$

To avoid $(n = 1, e = e_L)$ from being a dominated choice, we need another lower bound for λ. To see it, recall that $(n = 1, e = 0)$ is better than $(n = 1, e = e_L)$ if $z > \overline{z}_{fast}$, and $(n = 1, e = e_L)$ is better than $(n = 0, e = e_L)$ if $z > \underline{z}_{fast}$. $(n = 1, e = e_L)$ is therefore the best choice over the interval $(\underline{z}_{fast}, \overline{z}_{fast})$. For such an interval to exist, it must be the case that when $z = \underline{z}_{fast}$, $z < \overline{z}_{fast}$. $z = \underline{z}_{fast}$ means that the fast learners are indifferent between $(n = 1, e = e_L)$ and $(n = 0, e = e_L)$ so that

$$(1+r)a + wzx(h) + \frac{w'z'}{1+r'} = \exp(\frac{\chi_n}{1+\beta})\left[(1+r)a + \frac{w'z'}{1+r'}\right] \text{ if } h < h_M \frac{1}{1-\delta} \tag{A.8}$$

$$(1+r)a + wzx(h) + \frac{w'z'(1+\lambda)}{1+r'} = \exp(\frac{\chi_n}{1+\beta})\left[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}\right] \text{ if } h \geq h_M \frac{1}{1-\delta} \tag{A.9}$$

For the fast learners to prefer $(n = 1, e = e_L)$ over $(n = 1, e = 0)$, we need

$$(1+\beta)\ln \frac{c(n=1, e=e_L)}{c(n=1, e=0)} \geq \chi_e e_L \tag{A.10}$$

If $h < h_M \frac{1}{1-\delta}$, inequality (A.10) is:

$$(1+\beta)\ln \frac{(1+r)a + wzx(h) + \frac{w'z'}{1+r'}}{(1+r)a + wzx(h) + \frac{w'z'(1-\lambda)}{1+r'}} \geq \chi_e e_L$$

Evaluating the left-hand-side at $z = \underline{z}_{fast}$ yields:

$$\lambda \geq \underline{\lambda}_2 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}} \left(1 - \frac{1}{\exp(\frac{\chi_e e_L}{1+\beta})}\right) \exp(\frac{\chi_n}{1+\beta}) \tag{A.11}$$

If $h > h_M \frac{1}{1-\delta}$, inequality (A.10) is:

$$(1+\beta)\ln \frac{(1+r)a + wzx(h) + \frac{w'z'(1+\lambda)}{1+r'}}{(1+r)a + wzx(h) + \frac{w'z'}{1+r'}} \geq \chi_e e_L$$

Evaluating the left-hand-side at $z = \underline{z}_{fast}$ yields:

$$\lambda \geq \underline{\lambda}_4 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}} \frac{\left(\exp(\frac{\chi_e e_L}{1+\beta}) - 1\right)\exp(\frac{\chi_n}{1+\beta})}{\exp(\frac{\chi_e e_L}{1+\beta}) + \exp(\frac{\chi_n}{1+\beta}) - \exp(\frac{\chi_e e_L + \chi_n}{1+\beta})} \tag{A.12}$$

We have that $\underline{\lambda}_1 > \underline{\lambda}_2$ and $\underline{\lambda}_3 > \underline{\lambda}_4$ if

$$\exp(\frac{\chi_e e_H}{1+\beta}) > \frac{\exp(\frac{\chi_e e_L}{1+\beta})}{\exp(\frac{\chi_e e_L}{1+\beta}) + \exp(\frac{\chi_n}{1+\beta}) - \exp(\frac{\chi_e e_L + \chi_n}{1+\beta})} \tag{A.13}$$

Therefore, the inequality above implies that the conditions (A.6) and (A.7) are sufficient for the conditions (A.11) and (A.12). Furthermore, $\lambda_3 \geq \lambda_1$ so that the condition (A.7) is sufficient for the condition (A.6).

We can then conclude that the conditions (A.7) and (A.13) are sufficient for 1) the slower learners always prefers $(n = 0, e = e_H)$ over $(n = 0, e = 0)$, and 2) $\overline{z}_{fast} > \underline{z}_{fast}$, i.e., there exists state space where $(n = 1, e = e_L)$ is optimal.

A.3 Other cutoffs ranking for the two-period Model

For the fast learners, their cutoffs rank as follows

$$\frac{\overline{z}^L_{fast}(a)}{1-\lambda} > \overline{z}^L_{fast}(a) > \overline{z}^M_{fast}(a) > \frac{\overline{z}^M_{fast}(a)}{1+\lambda} \tag{A.14}$$

$$\frac{\underline{z}^L_{fast}(a)}{1-\lambda} > \underline{z}^M_{fast}(a) > \underline{z}^L_{fast}(a) > \frac{\underline{z}^M_{fast}(a)}{1+\lambda} \tag{A.15}$$

For the slow learners, the rank of their cutoffs is

$$\frac{\overline{z}^L_{slow}(a)}{1-\lambda} > \overline{z}^M_{slow}(a) > \overline{z}^L_{slow}(a) > \frac{\overline{z}^M_{slow}(a)}{1+\lambda} \tag{A.16}$$

For the non-learners, the rank of their cutoffs is

$$\frac{\overline{z}^L_{non}(a)}{1-\lambda} > \overline{z}^M_{non}(a) > \frac{\overline{z}^H_{non}(a)}{1+\lambda} > \frac{\overline{z}^M_{non}(a)}{1+\lambda} \tag{A.17}$$

$$\overline{z}^M_{non}(a) > \overline{z}^L_{non}(a) \tag{A.18}$$

B Proof of Proposition

B.1 Proof of Proposition 2

The derivative of saving with respect to t is

$$\frac{\partial a'^{\star}}{\partial t}(x,a;t) = -\frac{x\mu}{1+\beta} + \frac{x^2\Sigma}{\beta}\,\frac{t\,[2(x+a)+tx\mu]}{\big[(x+a)+tx\mu\big]^2}. \tag{B.1}$$

The total effect of on-job-training on saving is

$$\Delta_{\text{on-job}}(x,a;t) = a'^{\star}(x,a;t) - a'^{\star}(x,a;1) = \int_1^t \frac{\partial a'^{\star}}{\partial u}(x,a;u)du. \tag{B.2}$$

Define

$$F(x,a;u) \equiv x\,\frac{u[2(x+a)+ux\mu]}{[(x+a)+ux\mu]^2}, \quad \overline{F}(x,a;t) \equiv \frac{1}{t-1}\int_1^t F(x,a;u)du.$$

Then equation (B.2) can be written as

$$\Delta_{\text{on-job}}(x,a;t) = x(t-1)\Big[\frac{\Sigma}{\beta}\overline{F}(x,a;t) - \frac{\mu}{1+\beta}\Big].$$

Differentiating $F(x,a;u)$ with respect to x gives

$$\frac{\partial F(x,a;u)}{\partial x} = \frac{2u\,a\,(a+x)}{(a+(1+u\mu)x)^3} > 0,$$

so $\overline{F}(x,a;t)$ is strictly increasing in x.

The sign of $\Delta_{\text{on-job}}(x,a;t)$ is governed by

$$S(x,a;t) \equiv \frac{\Sigma}{\beta}\overline{F}(x,a;t) - \frac{\mu}{1+\beta}.$$

Because $\overline{F}(x,a;t)$ is strictly increasing, $S(x,a;t)$ increases monotonically with x.

For $x \to 0$, $F(x,a;u) \to 0$ and $\overline{F}(x,a;t) \to 0$ so that $S(x,a;t) \to -\frac{\mu}{1+\beta} < 0$, implying $\Delta_{\text{on-job}}(x,a;t) < 0$ for small x.

For $x \to \infty$, $F(x,a;u) \to \frac{u(2+u\mu)}{(1+u\mu)^2}$ and $\overline{F}(x,a;t) \to \overline{F}_\infty(t) \equiv \frac{1}{t-1}\int_1^t \frac{u(2+u\mu)}{(1+u\mu)^2}du$. If

$$\frac{\Sigma}{\mu} > \sigma^*(t) \equiv \frac{\beta}{1+\beta}\frac{1}{\overline{F}_\infty(t)} \tag{B.3}$$

then $S(x,a;t) > 0$ for sufficiently large x, and hence $\Delta_{\text{on-job}}(x,a;t) > 0$.

If idiosyncratic risk is large enough, i.e., condition (B.3) is satisfied, there exists a unique threshold $x^*(t)$ at which the sign flips:

$$\Delta_{\text{on-job}}(x,a;t) < 0 \text{ for } x < x^*(a,t), \qquad \Delta_{\text{on-job}}(x,a;t) > 0 \text{ for } x > x^*(a,t).$$

B.2 Proof of Lemma 1

Denote

$$G(x,a;t) \equiv \frac{t^2x^2}{(a+x+tx\mu)(a+tx\mu)}$$

the net additional effect of full-time training on saving can be rewritten as

$$\Delta_H(x,a;t) \equiv x\big[-\frac{\beta}{1+\beta} + \frac{\Sigma}{\beta}G(x,a;t)\big]$$

Differentiating $G(x,a;t)$ with respect to x gives

$$\frac{\partial G(x,a;t)}{\partial x} = \frac{t^2xa(2tx\mu+2a+x)}{(a+tx\mu)^2(a+x+tx\mu)^2} > 0,$$

so $G(x,a;t)$ is strictly increasing in x.

The limits of $G(x,a;t)$ are:

$$G(x,a;t) \to 0 \quad (x \to 0),$$
$$G(x,a;t) \to G_\infty(t) \equiv \frac{t}{\mu(1+t\mu)} \quad (x \to \infty),$$

Therefore, $G(x,a;t) < G_\infty(t)$ for any x.

If

$$\frac{\Sigma}{\beta}G_\infty(t) < \frac{\beta}{1+\beta}, \text{ i.e. } \frac{\Sigma}{\mu} < \hat{\sigma}(t) \equiv \frac{\beta^2}{1+\beta}(\frac{1}{t}+\mu). \tag{B.4}$$

Then $\Delta_H(x,a;t) < x[-\frac{\beta}{1+\beta} + \frac{\Sigma}{\beta}G_\infty(t)] < 0$ for any x. Furthermore, with some tedious algebra, we can show that for any x

$$G(x,a;t) + x\frac{\partial G(x,a;t)}{\partial x} < G_\infty(t)$$

Hence, the inequality (B.6) also implies that

$$\frac{\partial \Delta_H(x,a;t)}{\partial x} = \frac{\Sigma}{\beta}[G(x,a;t) + x\frac{\partial G(x,a;t)}{\partial x}] - \frac{\beta}{1+\beta} < \frac{\Sigma}{\beta}G_\infty(t) - \frac{\beta}{1+\beta} < 0. \quad \text{(B.5)}$$

If

$$\frac{\Sigma}{\beta}G_\infty(t) > \frac{\beta}{1+\beta}, \text{ i.e. } \frac{\Sigma}{\mu} > \hat{\sigma}(t) \equiv \frac{\beta^2}{1+\beta}(\frac{1}{t} + \mu), \quad \text{(B.6)}$$

since $G(x,a;t)$ is strictly increasing in x, there exists a unique $\hat{x}(a,t)$ such that

$$\Delta_H(x,a;t) = x\big[-\frac{\beta}{1+\beta} + \frac{\Sigma}{\beta}G(x,a;t)\big] > 0 \Leftrightarrow x > \hat{x}(a,t)$$

Moreover, $\Delta_H(x,a;t) > 0$ implies that

$$\frac{\partial \Delta_H(x,a;t)}{\partial x} > 0.$$

B.3 Proof of Proposition 4

The relevant upper bounds of z for positive human capital investment are functions of γ (to the first order approximation):

$$\begin{aligned}
\overline{z}^L_{slow}(a;\gamma) &= \overline{z}^L_{slow}(a;\gamma=0) - \gamma\lambda\frac{w'z'}{w(1+r')} \\
\overline{z}^L_{fast}(a;\gamma) &= \overline{z}^L_{fast}(a;\gamma=0) - \gamma\lambda\frac{w'z'}{w(1+r')}\frac{\exp(\frac{\chi_e e_L}{1+\beta})}{\exp(\frac{\chi_e e_L}{1+\beta})-1} \\
\overline{z}^M_{slow}(a;\gamma) &= \overline{z}^M_{slow}(a;\gamma=0) + \gamma\lambda\frac{w'z'}{w(1+r')}\exp(\frac{\chi_n - \chi_e e_H}{1+\beta}) \\
\overline{z}^M_{fast}(a;\gamma) &= \overline{z}^M_{fast}(a;\gamma=0) + \gamma\lambda\frac{w'z'}{w(1+r')}\frac{1}{\exp(\frac{\chi_e e_L}{1+\beta})-1}
\end{aligned}$$

Therefore, an anticipated AI shock, $\gamma > 0$ makes those with $h < h_M\frac{1}{1-\delta}$ invest less human capital and those with $h > h_M\frac{1}{1-\delta}$ invest more human capital.

B.4 Proof of Proposition 5

$$\Delta_{\text{on-job}}(x,a;t) = a'^{\star}(x,a;t) - a'^{\star}(x,a;1) = \int_1^t \frac{\partial a'^{\star}}{\partial u}(x,a;u)du.$$

differentiating with respect to t gives

$$\frac{d\Delta_{\text{on-job}}(x,a;t)}{dt} = \frac{\partial a'^{\star}}{\partial t}(x,a;t)$$

Since

$$\frac{\partial^2 a'^{*}(x,a;t)}{\partial t^2} = \frac{\partial}{\partial t}\left(-\frac{x\mu}{1+\beta} + \frac{x^2\Sigma}{\beta}\,\frac{t\,[2(x+a)+tx\mu]}{\big[(x+a)+tx\mu\big]^2}\right) = \frac{2x^2\Sigma(a+x)^2}{\beta(a+x+tx\mu)^3} > 0. \tag{B.7}$$

The slope $\frac{\partial a'^{\star}}{\partial t}(x,a;t)$ is strictly increasing in t. Hence $\Delta_{\text{on-job}}(x,a;t)$ is convex in t.

$$\Delta_H(x,a;t) = x\big[-\frac{\beta}{1+\beta} + \frac{\Sigma}{\beta}G(x,a;t)\big] \text{ with } G(x,a;t) = \frac{t^2x^2}{(a+x+tx\mu)(a+tx\mu)}$$

Differentiating $G(x,a;t)$ with respect to t gives

$$\frac{\partial G(x,a;t)}{\partial t} = \frac{tx^2(2a^2+2atx\mu+2ax+\mu t x^2)}{(a+tx\mu)^2(a+x+tx\mu)^2} > 0,$$

so $G(x,a;t)$ is strictly increasing in t, and so is $\Delta_H(x,a;t)$.

We now consider the comparison between $\Delta_{\text{on-job}}(x,a;t)$ and $\Delta_{\text{on-job}}(x,a;t')$ for $t' > t$. Given x and a, define

$$f(t) \equiv \frac{\partial a'^{*}}{\partial t}(x,a;t).$$

so $f'(t) > 0$, i.e. $f(t)$ is strictly increasing in t.

Case 1: $1 < t < t'$

Suppose $\Delta_{\text{on-job}}(x,a;t) > 0$. Then

$$\Delta_{\text{on-job}}(x,a;t) = \int_1^t f(u)\,du > 0.$$

Since f is increasing,

$$f(u) \le f(t) \quad \text{for all } u \in [1,t],$$

which implies

$$\Delta_{\text{on-job}}(x,a;t) = \int_1^t f(u)\,du \le (t-1)\,f(t).$$

Because $t > 1$, the inequality $\Delta_{\text{on-job}}(x,a;t) > 0$ forces $f(t) > 0$.

Now for any $t' > t$,

$$f(u) \ge f(t) > 0 \quad \text{for all } u \in [t,t'],$$

and therefore

$$\Delta_{\text{on-job}}(x, a; t') - \Delta_{\text{on-job}}(x, a; t) = \int_t^{t'} f(u)\, du > 0.$$

We then have that:

$$1 < t < t', \Delta_{\text{on-job}}(x, a; t) > 0 \quad \Longrightarrow \quad \Delta_{\text{on-job}}(x, a; t') > \Delta_{\text{on-job}}(x, a; t) \tag{B.8}$$

That is, once $\Delta_{\text{on-job}}(x, a; t)$ becomes positive for $t > 1$, it is strictly increasing in t thereafter.

Case 2: $t < t' < 1$

For $t < 1$,

$$\Delta_{\text{on-job}}(x, a; t) = \int_1^t f(u)\, du = -\int_t^1 f(u)\, du.$$

Suppose $\Delta_{\text{on-job}}(x, a; t) > 0$. Then

$$-\int_t^1 f(u)\, du > 0 \quad \Longrightarrow \quad \int_t^1 f(u)\, du < 0.$$

Since f is increasing

$$f(u) \geq f(t) \quad \text{for all } u \in [t, 1],$$

which implies

$$\int_t^1 f(u)\, du \geq (1 - t)\, f(t).$$

Because $t < 1$, the inequality $\Delta_{\text{on-job}}(x, a; t) > 0$ forces $f(t) < 0$.

Consider

$$\Delta_{\text{on-job}}(x, a; t') - \Delta_{\text{on-job}}(x, a; t) = \int_t^{t'} f(u)\, du$$

If $f(u) < 0$ for all $u \in [t, t']$, then $\int_t^{t'} f(u)\, du < 0$.

If there exists some $t_s \in [t, t']$ such that $f(t_s) = 0$, so $f(u) < 0$ for $u < t_s$ and $f(u) > 0$ for $u > t_s$. Then $f(u) > 0$ for $u \in [t', 1]$. Hence,

$$\int_{t'}^1 f(u)\, du > 0$$

This implies that

$$\Delta_{\text{on-job}}(x, a; t') = -\int_{t'}^1 f(u)\, du < 0$$

Together with the inequality $\Delta_{\text{on-job}}(x, a; t) > 0$, we have that

$$\Delta_{\text{on-job}}(x, a; t') < \Delta_{\text{on-job}}(x, a; t)$$

We then have that

$$t < t' < 1,\ \Delta_{\text{on-job}}(x, a; t) > 0 \quad \Longrightarrow \quad \Delta_{\text{on-job}}(x, a; t') < \Delta_{\text{on-job}}(x, a; t). \qquad \text{(B.9)}$$

Thus, for $t < 1$, whenever $\Delta_{\text{on-job}}(x, a; t) > 0$, increasing t toward 0 makes $\Delta_{\text{on-job}}$ strictly decrease.

C Computational Procedure for the Quantitative Model

C.1 Steady-state Equilibrium

In the steady-state, the measure of households, $\mu(a, h, z)$, and the factor prices are time-invariant. We find a time-invariant distribution μ. We compute the households' value functions and the decisions rules, and the time-invariant measure of the households. We take the following steps:

1. We choose the number of grid for the risk-free asset, a, human capital, h, and the idiosyncratic labor productivity, z. We set $N_a = 151$, $N_h = 151$, and $N_z = 9$ where N denotes the number of grid for each variable. To better incorporate the saving decisions of households near the borrowing constraint, we assign more points to the lower range of the asset and human capital.

2. Productivity z is equally distributed on the range $[-3\sigma_z/\sqrt{1-\rho_z^2}]$. As shown in the paper, we construct the transition probability matrix $\pi(z'|z)$ of the idiosyncratic labor productivity.

3. Given the values of parameters, we find the value functions for each state (a, h, z). We also obtain the decision rules: savings $a'(a, h, z)$, and $h'(a, h, z)$. The computation steps are as follow:

4. After obtaining the value functions and the decision rules, we compute the time-invariant distribution $\mu(a, h, z)$.

5. If the variables of interest are close to the targeted values, we have found the steady-state. If not, we choose the new parameters and redo the above steps.

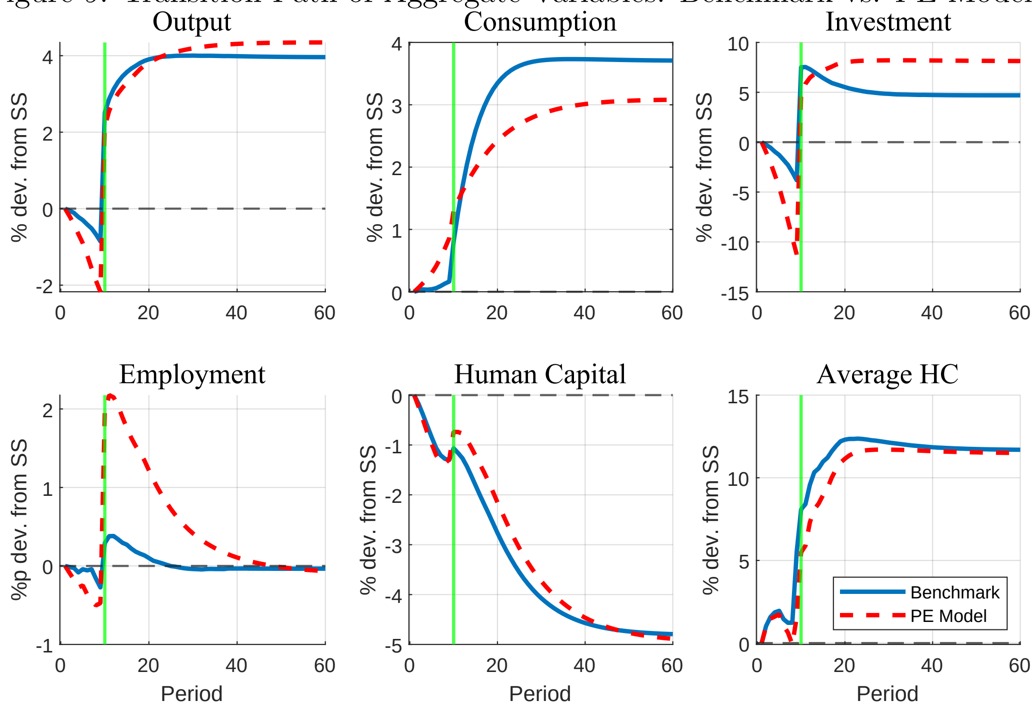
C.2 Transition Dynamics

We incorporate the transition path from the status quo to the new steady state. We describe the steps below.

1. We obtain the initial steady state and the new steady state.

2. We assume that the economy arrives at the new steady state at time T. We set the T to 100. The unit of time is a year.

Figure 9: Transition Path of Aggregate Variables: Benchmark vs. PE Models



Note: The transition paths of aggregate variables: benchmark vs. PE models. The x-axis represents years, and the y-axis shows the percentage deviation from the initial steady state. AI introduction is assumed to occur in period 10. The PE model is an economy in which factor prices are held fixed at their initial steady-state values until the new steady state is reached.

3. We initialize the capital-labor ratio $\{K_t/L_t\}_{t=2}^{T-1}$ and obtain the associated factor prices $\{r_t, w_t\}_{t=2}^{T-1}$.

4. As we know the value functions at time T, we can obtain the value functions and the decision rules in the transition path from $t = T - 1$ to 1.

5. We compute the measures $\{\mu_t\}_{t=2}^{T}$ with the measures at the initial steady state and the decision rules in the transition path.

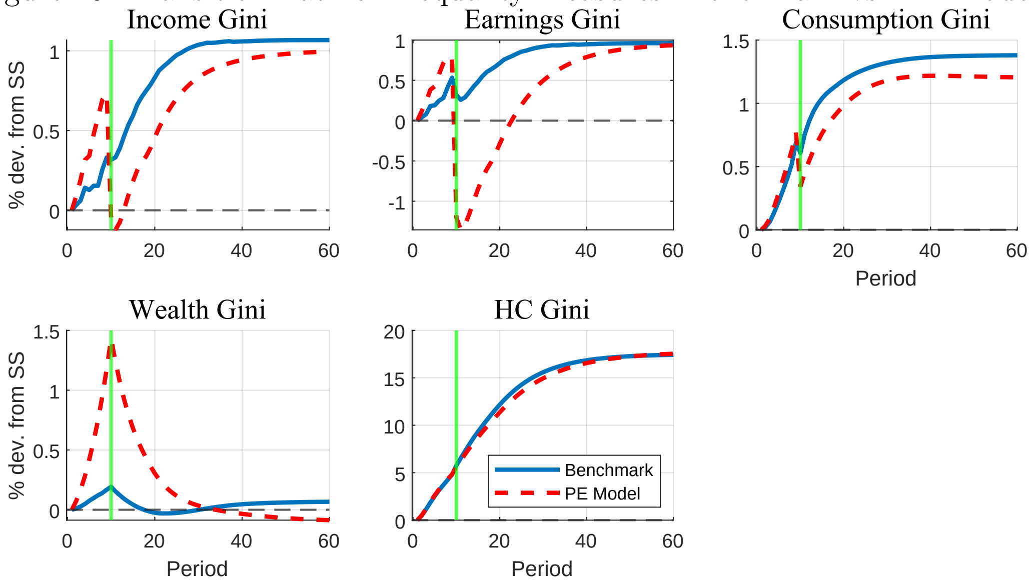
6. We obtain the aggregate variables in the transition path with the decision rules and the distribution measures.

7. We compare the assumed paths of capital and the effective labor with the updated ones. If the absolute difference between them in each period is close enough, we obtain the converged transition path. Otherwise, we assume new capital-labor ratio and go back to 3.

D Investigating the GE channel of AI's impact

Figures 9 and 10 compare the transition dynamics in the benchmark general-equilibrium model with those in a partial-equilibrium (PE) version of the model, where individual behavior responds to AI adoption but factor prices are held fixed at their initial steady-state values. The green vertical line marks the date of AI adoption.

Figure 10: Transition Path of Inequality Measures: Benchmark vs. PE Models



Note: The transition paths of inequality measures: benchmark vs. PE models. The x-axis represents years, and the y-axis shows the percentage deviation from the initial steady state. AI introduction is assumed to occur in period 10. The PE model is an economy in which factor prices are held fixed at their initial steady-state values until the new steady state is reached.

On the aggregate side (Figure 9), both models deliver a long-run expansion in output, consumption, and investment after AI adoption. In the PE model, GDP responses are quite similar across the two models, but the composition of that response differs. In the PE model, consumption rises by less, while investment rises by more in the long run. The reason is that, in the benchmark, the long-run return on capital becomes negative (as shown in Figure 6), whereas in the PE model there is no such price effect. As a result, households in the PE environment have stronger incentives to save and invest, tilting the response toward investment rather than consumption. Even though aggregate human-capital dynamics do not differ much across the two environments, employment behaves very differently around the adoption date. In the PE model, employment rises sharply when AI is introduced because wages do not fall as employment increases.

Turning to inequality dynamics (Figure 10), the long-run behavior is similar across the two environments, but the impact responses differ markedly. As noted above, employment rises more on impact in the PE model even though output responses are similar. This implies that the additional employment mainly comes from low-productivity households. Consequently, the Gini coefficients for income, earnings, and consumption fall more on impact in the PE model but then move toward levels similar to those in the benchmark once job polarization and skill reallocation take hold. The human-capital Gini shows virtually no difference between the two models. By contrast, the wealth Gini exhibits very different transition dynamics. In the PE model, it displays a pronounced but short-lived spike early in the transition because poor households save less, as wages do not fall there in response to AI adoption, unlike in the benchmark economy. In the long run, however, the wealth

Gini converges to a level similar to the benchmark, mainly because middle-sector households gradually increase their savings, as discussed in the main text.