

AI and Human Capital Accumulation: Aggregate and Distributional Implications*

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February 13, 2026

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 1 Introduction

² A defining feature of recent AI advancements is their ability to perform complex,
³ cognitive, non-routine tasks – capacities that once required substantial education
⁴ and expertise. This fundamental difference sets AI apart from earlier waves of au-
⁵ tomation or computerization, which primarily replaced manual or routine labor.¹ In
⁶ this paper, we make a central assumption – supported by a growing body of evidence
⁷ – that AI adoption reduces the premium for middle-level skills while increasing the
⁸ value of high-level expertise. Based on this assumption, we construct an incomplete
⁹ markets economy with endogenous asset accumulation and general equilibrium to
¹⁰ study how AI’s effects on skill premia interact with households’ human capital in-
¹¹ vestment, and their subsequent impact on aggregate and distributional outcomes of
¹² the economy.

¹³ 1.1 *Evidences for AI’s effects on skill premia*

¹⁴ Recent labor market data highlight the disproportionate impact of AI on entry-level
¹⁵ employment opportunities. Bloomberg (2025) reports that, in the words of Matt
¹⁶ Sigelman, president of the Burning Glass Institute, “Demand for junior hires in
¹⁷ many college-level roles is already declining, even as demand for experienced hires
¹⁸ in the same jobs is on the rise.” According to Revelio Labs (2025), postings for
¹⁹ entry-level jobs in the US declined by about 35% since January 2023, with roles
²⁰ more exposed to AI experiencing even steeper reductions.

²¹ Recent experimental evidence reviewed by Calvino *et al.*, (2025) shows that
²² workers’ productivity gains from AI depend on their skill levels and experience. On
²³ simpler tasks where AI performs well, the technology can narrow the productivity
²⁴ gap between experienced and less experienced workers. However, for more complex
²⁵ tasks that AI cannot yet perform effectively, those with greater digital proficiency
²⁶ or task-specific experience achieve higher productivity gains, as successful use of AI
²⁷ in these settings requires more advanced skills and experience that involves under-
²⁸ standing AI’s capabilities and limitations.

²⁹ Firm-level evidence reveals similar patterns. Aghion *et al.*, (2019) documents
³⁰ that the average worker in low-skilled occupations receives a significant wage pre-
³¹ mium when employed by a more innovative firm. Souza (2025) finds that the adop-
³² tion of AI in Brazilian firms increases employment for low-skilled production workers
³³ but reduces employment and wages for middle-wage office workers. Asam and Heller
³⁴ (2025) report that GitHub Copilot enables software startups to raise initial funding
³⁵ 19% faster with 20% fewer developers, and that these productivity gains dispropor-
³⁶ tionately benefit startups with more experienced founders.

¹For 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.

37 In anticipation of these changes, households are likely to adjust their human cap-
38 ital investments. A 2022 report by Higher Education Strategy Associates finds that
39 following decades of growth, dropping student enrollment in higher education has
40 become a major trend in the Global North (Higher Education Strategy Associates,
41 2022). In the U.S., the public across the political spectrum has increasingly lost
42 confidence in the economic benefits of a college degree.²

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

49 *1.2 Overview of our model and results*

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

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

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

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

²Pew 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.

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

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

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

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

104 Our findings reveal that human capital responses to AI amplify its positive effects
105 on aggregate output and consumption, but mitigate its positive effect on employ-
106 ment. While AI's direct effect on sectoral productivity reduces income and con-
107 sumption inequalities, job polarization resulting from human capital adjustments
108 reverses this effect and increases both inequalities.

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

113 the indirect effect from human capital responses partially offsets this increase.

114 1.3 Related Literature

115 This paper relates to the literature on how technological change, including AI and
116 robotics, drives job polarization and affects the demand and supply of labor. Studies
117 find that rising employment in both high- and low-wage occupations – at the expense
118 of middle-skill jobs – characterizes job polarization across the UK, US, and Western
119 Europe (Goos and Manning, 2007; Autor and Dorn, 2013; Goos *et al.*, 2014). Robots
120 and automation have also been shown to reduce employment and wages across US
121 regions (Acemoglu and Restrepo, 2020), with automation-induced job losses and
122 declining labor force participation especially concentrated among vulnerable workers
123 in highly automated sectors (Lerch, 2021; Faber *et al.*, 2022). Wang and Wong
124 (2025) models AI as a learning-by-using technology and predicts large productivity
125 gains and employment loss in the long-run.

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

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

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

150 A growing body of literature suggests that AI and automation may contribute to
151 rising inequality across income, consumption, and wealth (e.g., Sachs and Kotlikoff,

152 2012; Berg *et al.*, 2018; Prettner and Strulik, 2020; Hémous and Olsen, 2022).
153 Our model confirms that AI advancements indeed increase inequality in all three
154 dimensions. However, we find that the endogenous human capital responses to
155 AI amplify the rise in income and consumption inequality, while at the same time
156 mitigating the increase in wealth inequality.

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

164 2 Model Environment

165 Time is discrete and infinite. There is a continuum of households. Each household
166 is endowed with one unit of indivisible labor and faces idiosyncratic productivity
167 shock, z , that follows an AR(1) process in logs:

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

168 The asset market is incomplete following Aiyagari (1994), and the physical capital,
169 a , is the only asset available to households to insure against this idiosyncratic risk.
170 Households can also invest in human capital, h , which allows them to work in sectors
171 with different human capital requirement.

172 2.1 Production Technology

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

$$F(K, L) = K^{1-\alpha} L^\alpha \quad (2)$$

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

179 These sectors differ in their technologies for converting labor into effective labor
180 units and in the levels of human capital required for employment. The middle sector
181 employs households with human capital above h_M and converts one unit of labor
182 to one effective labor unit. The high sector, requiring human capital above h_H ,

¹⁸³ converts one unit of labor to $1 + \lambda$ effective units, while the low sector, with no
¹⁸⁴ human capital requirement, converts one unit into $1 - \lambda$ effective units. This implies
¹⁸⁵ a sectoral labor productivity $x(h)$ that is a step function in human capital:

$$x(h) = \begin{cases} 1 - \lambda & \text{low sector if } h < h_M \\ 1 & \text{middle sector if } h_M < h < h_H \\ 1 + \lambda & \text{high sector if } h > h_H \end{cases} \quad (3)$$

¹⁸⁶ A household i who decides to work thus contributes $z_i x(h_i)$ units of effective labor,
¹⁸⁷ where z_i is his idiosyncratic productivity. Denote $n_i \in \{0, 1\}$ as the indicator that
¹⁸⁸ takes one if the household works and zero if the household does not. The aggregate
¹⁸⁹ labor is

$$L = \int n_i z_i x(h_i) di, \quad (4)$$

¹⁹⁰ assuming perfect substitutability of effective labor across the three sectors.

¹⁹¹ 2.2 Household's Problem

¹⁹² Households derive utility from consumption, incur disutility from labor and effort of
¹⁹³ human capital investment. A household maximizes the expected lifetime utility by
¹⁹⁴ optimally choosing consumption, saving, labor supply and human capital investment
¹⁹⁵ each period, based on his idiosyncratic productivity shock z_t :

$$\max_{\{c_t, a_{t+1}, n_t, e_t\}_{t=0}^{\infty}} E_0 \left[\sum_{t=0}^{\infty} \beta^t (\ln c_t - \chi_n n_t - \chi_e e_t) \right] \quad (5)$$

¹⁹⁶ where c_t represents consumption, a_{t+1} represents saving, $n_t \in \{0, 1\}$ is labor supply,
¹⁹⁷ and e_t is the effort of human capital investment.

¹⁹⁸ If a household decides to work in period t , he will be employed into the appropriate
¹⁹⁹ sector according to his human capital h_t and receive labor income $w_t z_t x(h_t)$.
²⁰⁰ The household's budget constraint is

$$c_t + a_{t+1} = n_t (w_t z_t x(h_t)) + (1 + r_t) a_t \quad (6)$$

$$c_t \geq 0 \text{ and } a_{t+1} \geq 0 \quad (7)$$

²⁰¹ We prohibit households from borrowing $a_{t+1} \geq 0$ to simplify analysis.³

²⁰² Human capital investment can take three levels of effort: $\{0, e_L, e_H\}$. A non-
²⁰³ working household is free to choose any of the three effort levels but a working
²⁰⁴ household cannot devote the highest level of effort e_H , reflecting a trade-off between

³According to Aiyagari (1994), a borrowing constraint is necessarily implied by present value budget balance and nonnegativity of consumption. Since the borrowing limit is not essential to our analysis, we set it to zero for simplicity.

²⁰⁵ working and human capital investment. Hence:

$$e_t \in \{0, e_L, (1 - n_t)e_H\}. \quad (8)$$

²⁰⁶ Its contribution to next-period human capital is subject to the productivity shock:

$$h_{t+1} = z_t e_t + (1 - \delta_h) h_t \quad (9)$$

²⁰⁷ where δ_h is human capital's depreciation rate. We interpret $z_t e_t$ as effective human-
²⁰⁸ capital investment, with z_t capturing a learning-ability shock.⁴

²⁰⁹ 3 Household Decisions in a Two-Period Model

²¹⁰ In this section, we solve the household's problem with two periods to gain intuition.

²¹¹ **Period-2 decisions** Households do not invest in human capital or physical capital
²¹² in the last period. The only relevant decision is whether to work.

²¹³ The household works $n = 1$ if and only if $z \geq \bar{z}(h, a)$, with $\bar{z}(h, a)$ defined as

$$\ln(w\bar{z}(h, a)x(h) + (1 + r)a) - \chi_n = \ln((1 + r)a) \quad (10)$$

²¹⁴ The household faces a trade-off between earning labor income and incurring the
²¹⁵ disutility of working. Given the sector-specific productivity $x(h)$ specified in (3),
²¹⁶ the threshold for idiosyncratic productivity, $\bar{z}(h, a)$, takes on three possible values:

$$\bar{z}(h, a) = \begin{cases} \bar{z}(a)^{\frac{1}{1-\lambda}} & \text{if } h < h_M \\ \bar{z}(a) & \text{if } h_M \leq h < h_H \\ \bar{z}(a)^{\frac{1}{1+\lambda}} & \text{if } h > h_H \end{cases} \quad (11)$$

$$\text{where } \bar{z}(a) := \frac{(\exp(\chi_n) - 1)(1 + r)a}{w} \quad (12)$$

²¹⁷ Households with higher human capital is more likely to work, whereas households
²¹⁸ with higher physical capital is less likely to work.

²¹⁹ **Period-1 decisions** In addition to labor supply, period-1 decisions include saving
²²⁰ and human capital investment, both of which are forward-looking and affected by
²²¹ the idiosyncratic risk associated with the productivity shock z' . Our model also
²²² features a trade-off between human capital investment and labor supply as a working
²²³ household cannot devote the highest level of effort e_H in human capital investment.
²²⁴ Therefore, human capital investment grants households the possibility of a discrete
²²⁵ wage hike in the future but may entail a wage loss in the current period.

⁴Equivalently, one can think of an underlying learning-ability term that is perfectly correlated with z_t . This allows us to reduce the dimensionality of the state space.

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

231 *3.1 Period-1 Labor Supply and Human Capital Investment*

232 **3.1.1 Consumption and saving without uncertainty**

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

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

236 The log utility in consumption implies the optimality condition:

$$c' = \beta(1+r')c. \quad (13)$$

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

$$c(n, e) = \frac{1}{1+\beta} \left[(1+r)a + n(wzx(h)) + \frac{w'z'x(h' = ze + (1-\delta)h)}{1+r'} \right]. \quad (14)$$

239 **3.1.2 Labor supply and human capital investment**

240 The optimal consumption rules in (14) and (13) allow us to express the household's
 241 problem as the maximization of an objective function in labor supply n and human
 242 capital investment e :⁵

$$\max_{n,e} (1+\beta) \ln c(n, e) - \chi_n n - \chi_e e \quad (15)$$

243 This maximization depends critically on the household's current human capital and
 244 achievable next-period human capital. Accordingly, we partition households into
 245 five ranges of h : $[0, h_M]$, $[h_M, h_M(1-\delta)^{-1}]$, $[h_M(1-\delta)^{-1}, h_H]$, $[h_H, h_H(1-\delta)^{-1}]$,
 246 and $[h_H(1-\delta)^{-1}, h_{\max}]$.

247 We now derive the decision rules for households $h \in [h_M, h_M(1-\delta)^{-1}]$ in detail,
 248 as the decision rules for the other four ranges are similar. For households with

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

²⁴⁹ $h < h_M(1 - \delta)^{-1}$, we define two cutoffs in z :

$$\underline{z}_M(h) := \frac{h_M - (1 - \delta)h}{e_H}; \bar{z}_M(h) := \frac{h_M - (1 - \delta)h}{e_L} \quad (16)$$

²⁵⁰ These cutoffs divide households into three groups based on their ability to be em-
²⁵¹ ployed in the middle sector in the next period.

²⁵² **Non-learners** are households with $z < \underline{z}_M(h)$. They cannot achieve $h' > h_M$
²⁵³ with either e_L or e_H level of human capital investment today. As a result, they will
²⁵⁴ choose not to invest in human capital, $e = 0$, and their future sectoral productivity
²⁵⁵ will be $x(h') = 1 - \lambda$. These non-learners work $n = 1$ if and only if $z \geq \bar{z}_{non}^L(a)$:

$$\bar{z}_{non}^L(a) = \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1 + r)a + \frac{w'z'(1-\lambda)}{1+r'}]}{w} \quad (17)$$

²⁵⁶ **Slow learners** are households with $z \in (\underline{z}_M(h), \bar{z}_M(h))$. These households can
²⁵⁷ reach $h' > h_M$ in the next period only by investing $e = e_H$ today. Their choice
²⁵⁸ is restricted to $e = 0$ or $e = e_H$, since selecting $e = e_L$ incurs a cost without any
²⁵⁹ future benefit. Slow learners must trade off between working and human capital
²⁶⁰ investment: choosing $e = e_H$ requires not working today ($n = 0$), while opting to
²⁶¹ work means forgoing investment in human capital ($n = 1, e = 0$).⁶

²⁶² Slow learners prefer $(n = 1, e = 0)$ to $(n = 0, e = e_H)$ if and only if $z \geq \bar{z}_{slow}^L(a)$:

$$\bar{z}_{slow}^L(a) = \frac{(\exp(\frac{\chi_n - \chi_e e_H}{1+\beta}) - 1)[(1 + r)a + \frac{w'z'}{1+r'}] + \lambda \frac{w'z'}{1+r'}}{w} \quad (18)$$

²⁶³ **Fast learners** are households with $z > \bar{z}_M(h)$. They can achieve $h' > h_M$ in
²⁶⁴ the next period if they invest $e = e_L$ today. In this case, there is no need to exert
²⁶⁵ high effort e_H in human capital investment. The fast learners choose among three
²⁶⁶ options: $(n = 1, e = 0)$, $(n = 1, e = e_L)$, and $(n = 0, e = e_L)$.⁷

²⁶⁷ The decision rule for fast learners are as follows:

$$n(z, h, a), e(z, h, a) = \begin{cases} n = 1, e = 0 & \text{if } z \geq \bar{z}_{fast}^L(a) \\ n = 1, e = e_L & \text{if } \underline{z}_{fast}^L(a) \leq z < \bar{z}_{fast}^L(a) \\ n = 0, e = e_L & \text{if } z < \underline{z}_{fast}^L(a) \end{cases} \quad (19)$$

⁶The 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 .

⁷Similar 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 $(n = 0, e = 0)$.

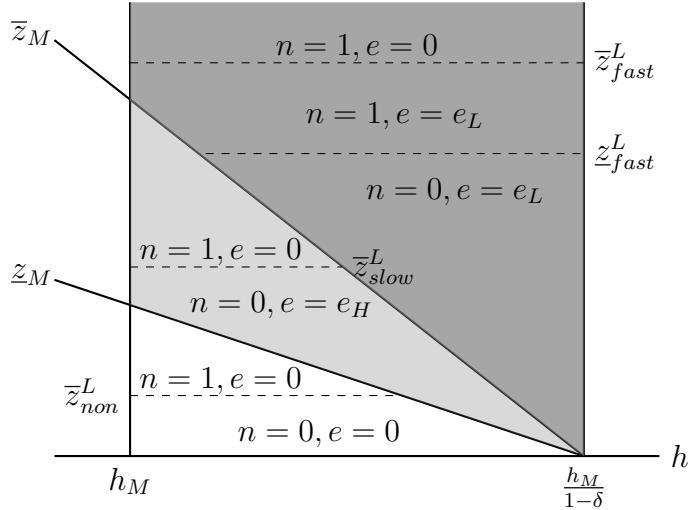


Figure 1: Decision Rule Diagram for $h_M \leq h < h_M(1 - \delta)^{-1}$

The human capital h changes along the horizontal line and the idiosyncratic productivity z changes along the vertical line. The two diagonal lines, $\bar{z}_M(h)$ and $\underline{z}_M(h)$, separate the state space into three areas: the unshaded area represents the non-learners, the lightly-shaded area represents the slow learners, and the darkly-shaded area represents the fast learners. The areas are divided by four dashed horizontal lines associated with cutoffs \bar{z}_{non}^L , \bar{z}_{slow}^L , \underline{z}_{fast}^L , and \bar{z}_{fast}^L that are functions of capital holding a .

²⁶⁸ where

$$\bar{z}_{fast}^L(a) = \frac{\left\{ \exp(\frac{\chi_e e_L}{1+\beta}) \lambda \left[\exp(\frac{\chi_e e_L}{1+\beta}) - 1 \right]^{-1} - 1 \right\} \frac{w' z'}{1+r'} - (1+r)a}{w} \quad (20)$$

²⁶⁹

$$\underline{z}_{fast}^L(a) = \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w' z'}{1+r'}]}{w} \quad (21)$$

²⁷⁰ We set up our model so that $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.⁸

²⁷¹ **Decision rule diagram:** Figure 1 illustrates the decision rule (n, e) as a function
²⁷² of states (z, h, a) for households with $h_M \leq h < h_M \frac{1}{1-\delta}$. The human capital h
²⁷³ changes along the horizontal line and the idiosyncratic productivity z changes along
²⁷⁴ the vertical line. The two diagonal lines, $\bar{z}_M(h)$ and $\underline{z}_M(h)$ defined in (16), separate
²⁷⁵ the state space into three areas: the unshaded area represents the non-learners,
²⁷⁶ the lightly-shaded area represents the slow learners, and the darkly-shaded area
²⁷⁷ represents the fast learners. The areas are divided by four dashed horizontal lines
²⁷⁸ associated with cutoffs $\bar{z}_{non}^L(a)$, $\bar{z}_{slow}^L(a)$, $\underline{z}_{fast}^L(a)$, and $\bar{z}_{fast}^L(a)$ that are functions of
²⁷⁹ capital holding a and defined in (17), (18), (21), and (20).

²⁸⁰ This decision rule diagram is representative for households in other four ranges

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 $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.

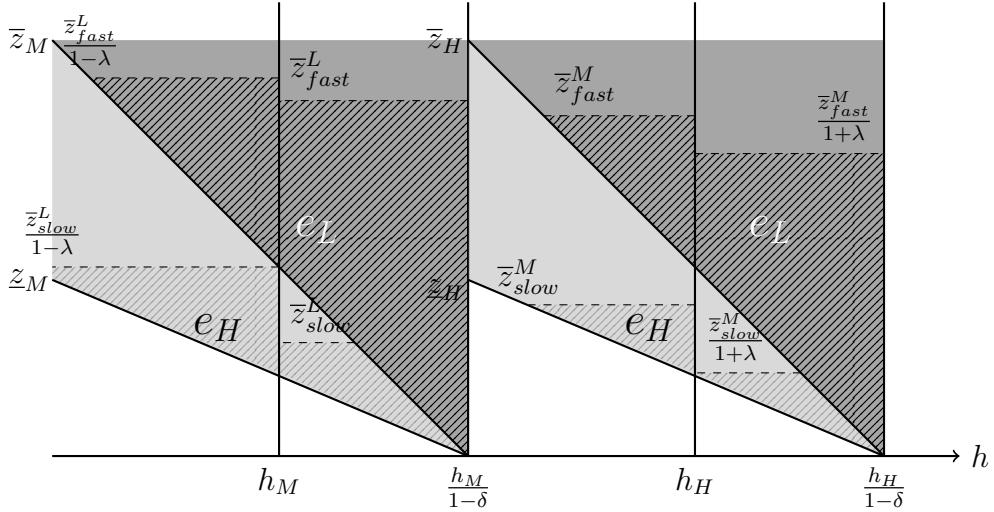


Figure 2: State Space for Human Capital Investment

The darkly-shaded striped areas indicate the state space for human capital investment equal to e_L by the fast learners. The lightly-shaded striped areas indicate the state space for human capital investment equal to e_H by the slow learners.

of human capital. Figure 2 illustrates the regions in which households make positive human capital investments. Striped shading highlights where investment occurs, with dark areas denoting fast learners and light areas representing slow learners.

For households with $h < h_M$, $\bar{z}_M(h)$ and $\underline{z}_M(h)$ continue to be the boundaries that separate non-learners, slow learners and fast learners, but the four cutoffs are $\bar{z}_{non}^L \frac{1}{1-\lambda}$, $\bar{z}_{slow}^L \frac{1}{1-\lambda}$, $\underline{z}_{fast}^L \frac{1}{1-\lambda}$, and $\bar{z}_{fast}^L \frac{1}{1-\lambda}$.

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

$$\underline{z}_H(h) := \frac{h_H - (1-\delta)h}{e_H}; \quad \bar{z}_H(h) := \frac{h_H - (1-\delta)h}{e_L} \quad (22)$$

If $h_M \frac{1}{1-\delta} \leq h < h_H$, the four cutoffs that partition the decision regions for households are denoted as $\bar{z}_{non}^M(a)$, $\bar{z}_{slow}^M(a)$, $\underline{z}_{fast}^M(a)$, and $\bar{z}_{fast}^M(a)$ (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 $\bar{z}_{non}^M \frac{1}{1+\lambda}$, $\bar{z}_{slow}^M \frac{1}{1+\lambda}$, $\underline{z}_{fast}^M \frac{1}{1+\lambda}$, and $\bar{z}_{fast}^M \frac{1}{1+\lambda}$.

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 $\bar{z}_{non}^H(a) \frac{1}{1+\lambda}$ matters.

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 \bar{z}' and variance σ_z^2 .

⁹ Appendix A.2 provides parameter restrictions for $\bar{z}_{fast}^M(a) > \underline{z}_{fast}^M(a)$.

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

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

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

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

324 **Proposition 1.** *The uninsured idiosyncratic risk in z' makes households in period
 325 1 save more, work more and invest less in human capital.*

326 3.3 Period-1 Saving and Human Capital Investment

327 In this section, we study the impact of endogenous human capital investment on
 328 households' saving decisions. Specifically, we compare optimal saving behavior in
 329 two scenarios: one in which households can choose to invest in human capital, and

¹⁰The 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.

330 an alternative scenario in which human capital is exogenously fixed. To facilitate the
 331 comparison, we assume in this section that there is no human capital depreciation.¹¹

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

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

340 In particular, the household maximizes expected lifetime utility:

$$\max_{a'} : \ln(c) + \beta \mathbb{E}_{z'}[\ln(c')], \quad (23)$$

341 subject to the budget constraints

$$c + a' = (1 + r)a + n(wzx(h)), \quad (24)$$

$$c' = (1 + r')a' + w'z'x(h'), \quad (25)$$

$$\text{with } h' = ze + (1 - \delta)h, e \in \{0, e_L, (1 - n)e_H\} \quad (26)$$

342 3.3.1 Effect of on-job-training on saving

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

346 To simplify the notation while maintaining the key economic forces, we normalize
 347 $(1 + r) = (1 + r') = 1$, $w = w' = 1$, the period-1 productivity shock $z = 1$ and the
 348 period-2 productivity shock z' to $\ln z' \sim \mathcal{N}(0, \sigma_z^2)$. The budget constraints become:

$$c + a' = a + x, \quad c' = a' + txz' \quad (27)$$

349 where x is the household's period-1 labor income that reflects both productivity and
 350 skill. $t \geq 1$ represents the effect of human capital investment on period-2 income:
 351 $t > 1$ if $e = e_L$; $t = 1$ if $e = 0$.

¹¹If depreciation is allowed, the analysis proceeds similarly but involves more comparison pairs.

¹²Why 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 $(n = 0, e = e_L \text{ or } e_H)$ 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.

352 The optimal saving is determined by the FOC:

$$\frac{1}{a+x-a'} = \beta \mathbb{E}_{z'} \left(\frac{1}{a'+txz'} \right) \quad (28)$$

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

$$\mu \equiv \mathbb{E}[z'] = e^{\sigma_z^2/2}, \quad \Sigma \equiv \text{Var}(z') = e^{\sigma_z^2} (e^{\sigma_z^2} - 1). \quad (29)$$

354 The second-order approximate solution to the FOC is:

$$a'^*(x, a; t) = \underbrace{\frac{\beta(a+x) - tx\mu}{1+\beta}}_{\text{CE}} + \underbrace{\frac{t^2 x^2 \Sigma}{\beta(a+x+tx\mu)}}_{\text{Precautionary}} \quad (30)$$

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

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

$$\frac{\partial a'^*}{\partial t}(x, a; t) = -\frac{x\mu}{1+\beta} + \frac{x^2 \Sigma}{\beta} \frac{t[2(a+x) + tx\mu]}{(a+x+tx\mu)^2}. \quad (31)$$

361 The first term being negative captures the *crowd-out* effect on saving via consumption-
 362 smoothing motive as on-job-training increases the expected period-2 labor income
 363 $tx\mu$. The second positive term captures the *crowd-in* effect via precautionary saving
 364 motive as on-job-training exposes households to larger future income risk.

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

$$\Delta_{\text{on-job}}(x, a; t) = a'^*(x, a; t) - a'^*(x, a; 1) = \int_1^t \frac{\partial a'^*}{\partial u}(x, a; u) du, \quad (32)$$

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

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

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

³⁷⁷ $x > x^*(a, t)$, $e = e_L$ raises saving $\Delta_{\text{on-job}}(x, a; t) > 0$.

³⁷⁸ *Proof.* See Appendix B. □

³⁷⁹ 3.3.2 Effect of full-time training on saving

³⁸⁰ We next compare the optimal saving between $(n = 0, e = e_L \text{ or } e_H)$ and $(n =$
³⁸¹ $1, e = 0)$. Note that full-time training requires the households to give up their labor
³⁸² income in period 1, which is not the case for on-job-training. Following the same
³⁸³ normalization and notation as in the previous subsection, we can write the budget
³⁸⁴ constraints with full-time training and without training as:

$$e = e_H : c + a' = a, \quad c' = a' + txz' \quad (33)$$

$$e = 0 : c + a' = a + x, \quad c' = a' + xz' \quad (34)$$

³⁸⁵ where $t > 1$ captures the effect of full-time training on period-2 income.

³⁸⁶ The second-order approximation to the optimal saving problem yields:

$$e = e_H : a'^*_H(x, a; t) = \underbrace{\frac{\beta a - tx\mu}{1 + \beta}}_{\text{CE}} + \underbrace{\frac{t^2 x^2 \Sigma}{\beta(a + tx\mu)}}_{\text{Precautionary}} \quad (35)$$

$$e = 0 : a'^*(x, a; 1) = \underbrace{\frac{\beta(a + x) - x\mu}{1 + \beta}}_{\text{CE}} + \underbrace{\frac{x^2 \Sigma}{\beta(a + x + x\mu)}}_{\text{Precautionary}} \quad (36)$$

³⁸⁷ The overall effect of full-time training on saving can be expressed as:

$$\begin{aligned} \Delta_{\text{full-time}}(x, a; t) &= a'^*_H(x, a; t) - a'^*(x, a; 1) \\ &= \Delta_{\text{on-job}}(x, a; t) + \Delta_H(x, a; t) \end{aligned} \quad (37)$$

$$\text{where } \Delta_H(x, a; t) \equiv x \left[-\frac{\beta}{1 + \beta} + \frac{\Sigma}{\beta} \frac{t^2 x^2}{(a + x + tx\mu)(a + tx\mu)} \right] \quad (38)$$

³⁸⁸ Here, $\Delta_H(x, a; t)$ captures the additional impact of full-time training on saving, over
³⁸⁹ and above that of on-job-training. The first term reflects a further reduction in
³⁹⁰ saving due to the need to forgo period-1 labor income. The second term shows
³⁹¹ an increase in precautionary saving, as reduced current resources limit households'
³⁹² ability to self-insure against idiosyncratic risk in period 2.

³⁹³ The following lemma establishes some properties of $\Delta_H(x, a; t)$:

³⁹⁴ **Lemma 1.** *If $\frac{\Sigma}{\mu} < \hat{\sigma}(t)$, $\Delta_H(x, a; t) < 0$ and decreases in x . If $\frac{\Sigma}{\mu} > \bar{\sigma}(t)$, $\Delta_H(x, a; t) >$
³⁹⁵ 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 .*

³⁹⁶ *Proof.* See Appendix B. □

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

400 **Proposition 3.** *If the idiosyncratic risk is large enough, i.e., $\frac{\Sigma}{\mu} > \max\{\sigma^*(t), \hat{\sigma}(t)\}$,
 401 full-time training crowds out saving for low-income households and crowds in sav-
 402 ing for high-income households: for $x < \min\{x^*(a, t), \hat{x}(a, t)\}$, $e = e_H$ lowers
 403 saving $\Delta_{full-time}(x, a; t) < 0$; for $x > \max\{x^*(a, t), \hat{x}(a, t)\}$, $e = e_H$ raises saving
 404 $\Delta_{full-time}(x, a; t) > 0$.*

405 3.4 The Effects of an Anticipated Period-2 AI Shock

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

$$x(h') = \begin{cases} 1 - \lambda + \gamma\lambda & \text{low sector if } h' < h_M \\ 1 & \text{middle sector if } h_M < h' < h_H \\ 1 + \lambda + \gamma\lambda & \text{high sector if } h' > h_H \end{cases} \quad (39)$$

409 In other words, the AI shock increases average labor productivity, reduces the earn-
 410 ings premium for the middle sector, and enlarges the earnings premium for the high
 411 sector relative to the middle sector.

412 3.4.1 Effects on human capital investment

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

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

423 *Proof.* See Appendix B. □

424 3.4.2 Effects on labor supply

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

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

435 **3.4.3 Effects on saving**

436 The AI shock increases sectoral labor productivity for the low and high sectors in
 437 period 2, while leaving the middle sector's labor productivity unchanged. Its effect
 438 on saving can be analyzed as if we are varying the parameter t in the functions
 439 $\Delta_{\text{on-job}}(x, a; t)$, defined in (32), and $\Delta_H(x, a; t)$, defined in (38).

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

- 441 • 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 $t' > t > 1$.
- 442 • 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 $1 > t' > t$.

443 *Proof.* See Appendix B. □

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

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

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

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

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

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

469 For the middle-sector households who upskill via full-time training, there is an
470 *additional positive effect* of the AI shock on their saving, because a higher x' increases
471 $\Delta_H(x, a; t)$ (Proposition 5).

472 **Households who downskill** Downsampling, which reflects human capital depre-
473 ciation, does not require any new investment in skills. For high-sector households
474 who transition downward, the AI shock leaves their future productivity – and thus
475 their saving – unchanged.

476 For middle-sector households who downskill to the low sector, their saving differs
477 from the fixed human capital scenario by $\Delta_{\text{on-job}}(x, a; t)$ with $t < 1$. The AI shock
478 mitigates their future productivity loss by reducing it from λ to $(1 - \gamma)\lambda$, effectively
479 increasing t to a new value $t' < 1$. According to Proposition 5, if the pre-shock effect
480 $\Delta_{\text{on-job}}(x, a; t)$ is positive, the AI shock will *reduce* saving. If this effect is negative,
481 however, the overall impact of the AI shock on saving is ambiguous.

482 3.5 Limitations of the two-period model

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

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

497 **Composition effects** Endogenizing human capital investment injects dynamism
498 into how households sort themselves among the three skill sectors. When an AI shock

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
\bar{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

499 occurs, individuals may choose to retrain, upskill, or even move to lower-skilled work,
 500 reshaping the distribution of labor across sectors. This shifting composition changes
 501 the relative size of each sector, with significant consequences for both aggregate
 502 outcomes and the distributional effects of AI.

503 4 A Quantitative Model

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

507 4.1 Calibration

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

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

516 We calibrate parameters regarding labor productivity process as follows. We
 517 assume that z follows the AR(1) process in logs: $\log z' = \rho_z \log z + \epsilon_z$, where $\epsilon_z \sim$
 518 $N(0, \sigma_z^2)$. The shock process is discretized using the **tauchen1986finite** method,
 519 resulting in a transition probability matrix with 11 grids. We set the persistence

520 parameter to $\rho_z = 0.948$ and the standard deviation to $\sigma_z = 0.269$, following the
521 estimates reported in Chang and Kim (2006).

522 We deviate from the two-period model by assuming that the labor supply is a
523 discrete choice between 0 and $\bar{n} = 1/3$. This change only rescales the two-period
524 model without altering the trade-off facing the households. But such rescaling facil-
525 itates the interpretation that households are deciding whether to allocate one-third
526 of their fixed time endowment to work. The high-level human capital accumulation
527 effort, e_H is assumed to equal \bar{n} . The low-level effort, e_L is set to half of e_H . The skill
528 premium across sectors, λ , is set at 0.2 to match the earnings Gini coefficient. Hu-
529 man capital cutoffs, h_M and h_H , are set so that the population shares in low, middle,
530 and high sectors are, respectively, 20, 40, and 40 percent. This population distri-
531 bution roughly matches the fractions of U.S. workers in 2014 who are employed in
532 routine manual occupations (low sector), routine cognitive and non-routine manual
533 (middle sector), and non-routine cognitive (high sector) (Cortes *et al.*, 2017).

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

537 4.2 Key Moments: Data vs. Model

538 In Table II, we present a comparison of key moments between the model and the
539 empirical data. The model does an excellent job of replicating the 80% employment
540 rate observed in the data. In this context, employment is defined as having posi-
541 tive labor income in the given year, consistent with the common approach used in
542 the literature. According to **oecd2025adultlearning**, the share of the population
543 investing in human capital—those who are actively engaged in skill acquisition or
544 education—is approximately 30%, a figure well matched by the model’s predictions.
545 This is an important metric because it reflects the model’s capacity to capture the
546 dynamics of human capital formation, which plays a critical role in shaping long-run
547 earnings and income inequality. Additionally, the model accurately captures the dis-
548 tribution of income and earnings, aligning closely with observed data. This suggests
549 that the model effectively incorporates the key mechanisms driving labor market
550 outcomes and the corresponding distributional aspects of earnings. Although the
551 model does not explicitly target the wealth Gini coefficient, it achieves a close match
552 to the data: the empirical wealth Gini is 0.78, while the model produces a value of
553 0.76. This highlights the model’s ability to capture substantial wealth inequality in
554 the economy.

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

555 4.3 Steady-state Distribution

556 Table III presents the steady-state distribution of population, employment, and
 557 assets across sectors. The population shares are calibrated to 20%, 40%, and
 558 40% by adjusting the human capital thresholds that define sectors. The shares
 559 of employment and assets are endogenously determined by households' labor supply
 560 and savings decisions. Notably, the high sector accounts for 46% of total employ-
 561 ment—exceeding its population share—indicating that a disproportionate number
 562 of households choose to work in that sector. Asset holdings are even more skewed:
 563 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

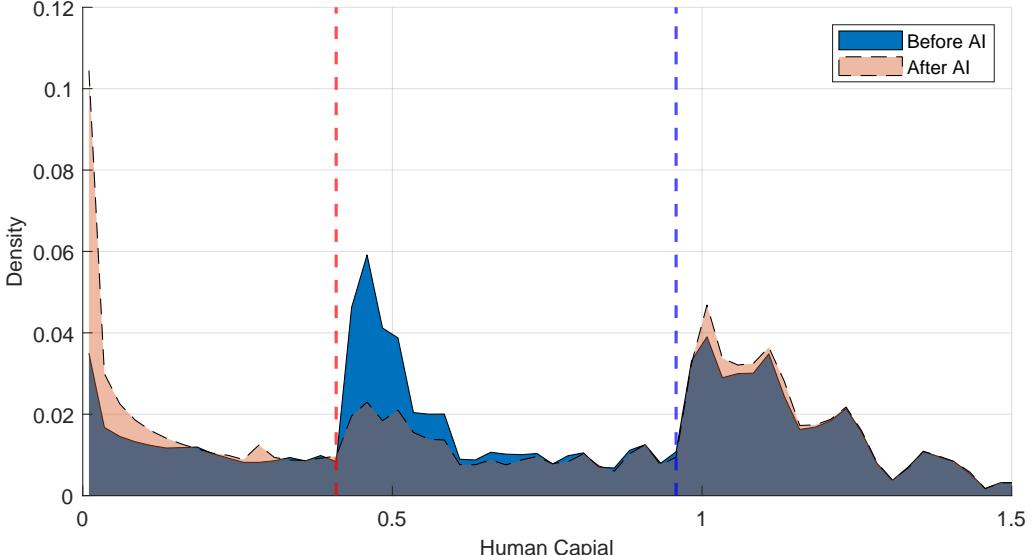
Note: Human capital cutoffs, h_H and h_M , determine the population share across sectors. Employment share and assets share are implied by households labor supply decisions and saving decisions.

564 5 AI's Impact on Human Capital Adjustments

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

570 The effect of AI on the sectorial productivity is modeled as in (39) with $\gamma = 0.3$.
 571 That is, AI boosted the productivity of the low sector workers by 7.5% and the
 572 productivity of the high sector workers by 5%, leaving the middle sector intact.
 573 It captures the key idea that AI increases average labor productivity (Acemoglu
 574 and Restrepo, 2019), but reduces the earning premium for the middle sector, and
 575 enlarges the earning premium for the higher sector relative the middle sector.

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.

576 5.1 Human Capital Adjustments

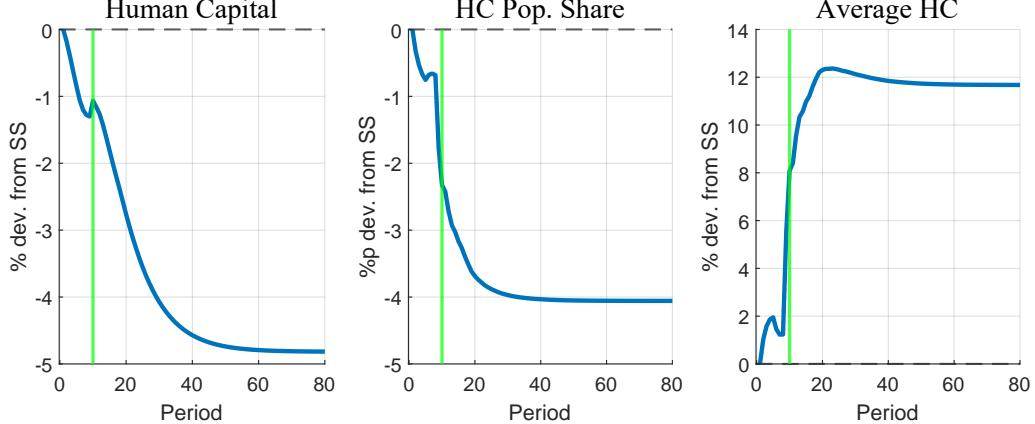
577 Given the employment distribution in the initial steady state, AI is projected to
 578 increase the economy's labor productivity by 4% on average, assuming households
 579 do not alter their decisions in response. However, changes in earning premiums
 580 incentivize households to adjust their human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

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

587 The gray shaded area shows the overlap between the two steady-state distri-
 588 butions. Within each sector, the distribution of households is skewed to the left,
 589 reflecting the tendency for human capital investment to be concentrated among
 590 those near the sectoral cutoffs. As shown in the decision rule diagram in Figure 2,
 591 some households seek to upgrade their skills, while others aim to remain in more
 592 skilled sectors. The blue shaded area highlights the mass of households who have
 593 exited the middle sector following the AI shock. The pink areas represent the addi-
 594 tional mass of households in the new steady-state distribution, concentrated at the
 595 lower end of the low sector and the lower end of the high sector.

596 **Transition path** Figure 4 reports the transition dynamics of aggregate human
 597 capital from the initial to the new steady state. The figure also displays its extensive

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.

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 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 dis-

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

621 proportionately replace tasks commonly performed by middle-skilled workers. How-
622 ever, our model introduces a complementary mechanism to the conventional under-
623 standing of this reallocation. Specifically, households in our model voluntarily exit
624 the middle sector even before AI implementation by adjusting their human capital
625 investments – many middle-sector workers opt for non-employment to invest in skills
626 that will better position them for the post-AI labor market.¹⁴ This mechanism is
627 formally characterized in Proposition (4) in the two period model above.

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

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

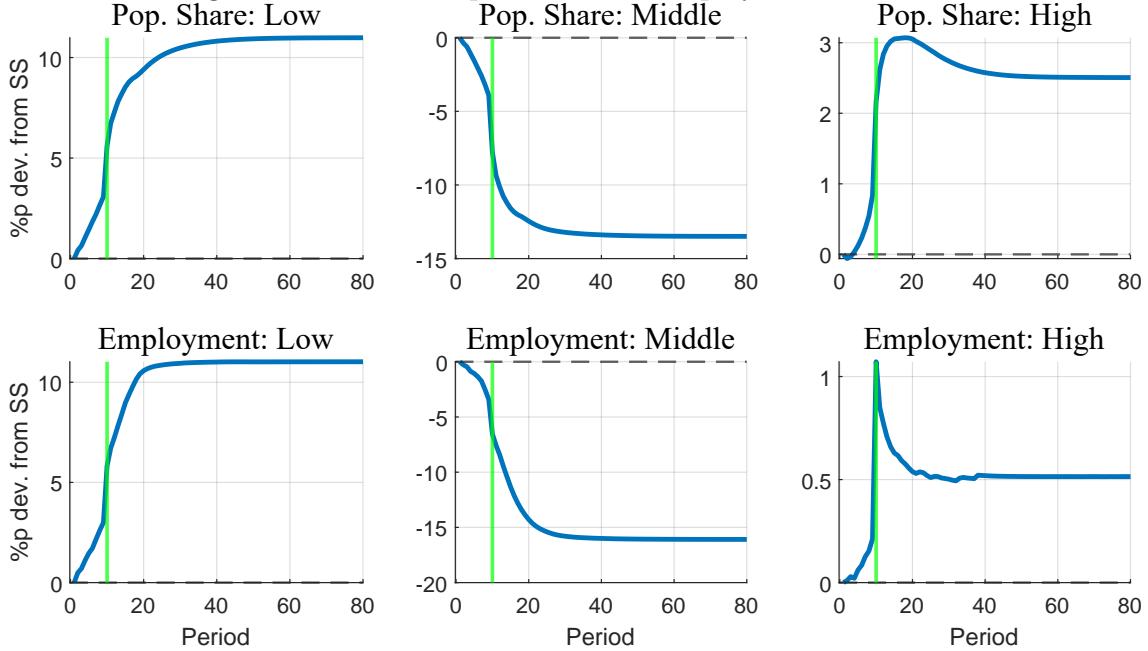
644 **6 The Aggregate and Distributional Effects of AI**

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

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

¹⁴To 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.

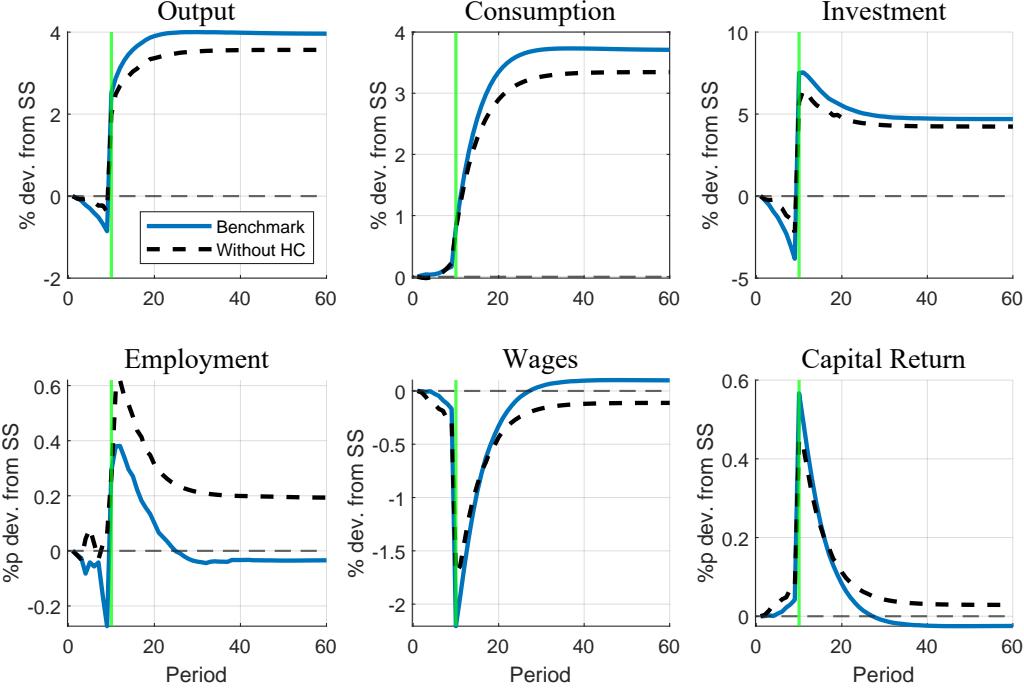
657 In this section, we examine the importance of endogenous human capital ad-
 658 justment in shaping both the transitional and long-run effects of AI. To do so, we
 659 compare the benchmark economy – where households endogenously adjust their hu-
 660 man capital – with an alternative scenario in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

664 By contrasting the transition dynamics across these two economies, we can disen-
 665 tangle the direct and indirect effects of AI. The transition path in the No-HC-model
 666 isolates the direct impact of AI on aggregate and distributional outcomes, as it ab-
 667 stracts from any human capital adjustments. The difference in outcomes between
 668 the benchmark and the No-HC-model then reveals the indirect effects of AI that
 669 operate through households’ adjustments in human capital. This decomposition al-
 670 lows us to assess the relative importance of human capital dynamics in driving both
 671 the aggregate and distributional consequences of AI.

672 6.1 Aggregate Implications

673 Figure 6 shows the transition paths of key macroeconomic variables—output, con-
 674 sumption, investment, and employment—as well as factor prices, including the wage
 675 rate and capital return. The blue solid lines depict results from the benchmark model
 676 with endogenous human capital adjustment, while the black dashed lines represent

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.

677 the No-HC model in which human capital is held fixed.

678 6.1.1 AI's direct impacts

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

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

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

697 higher.

698 6.1.2 AI's indirect impacts via endogenous human capital adjustments

699 The difference between the No-HC model and the benchmark model captures the
700 indirect effects of AI operating through endogenous human capital adjustments.

701 Among all macroeconomic variables, this indirect effect is most pronounced for em-
702 ployment.

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

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

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

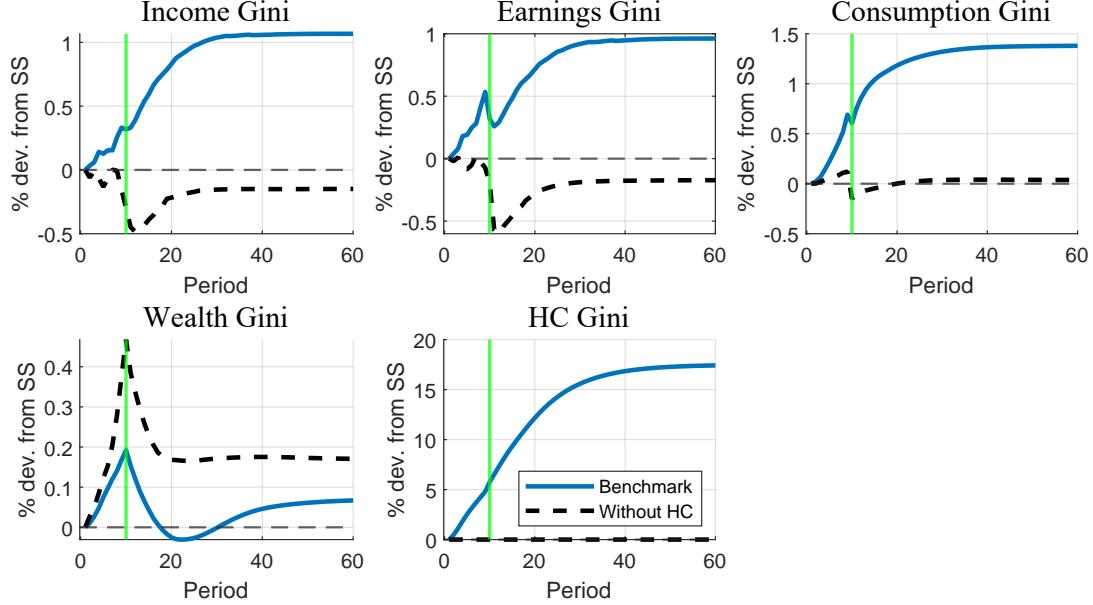
721 6.2 Distributional Implications

722 The findings above underscore the importance of accounting for human capital ad-
723 justments when assessing the aggregate impact of AI, as households actively adapt
724 to a rapidly evolving labor market. When it comes to economic inequality, endoge-
725 nously adjusting human capital plays an even more significant role.

726 Figure 7 shows the transition paths of Gini coefficients for earnings (labor in-
727 come), total income (capital and labor income), consumption, wealth (asset hold-
728 ings), and human capital. The black dashed lines represent results from the No-HC
729 model, capturing the direct impact of AI without human capital adjustment. In
730 contrast, the blue solid lines reflect the benchmark model, where human capital re-
731 sponds endogenously to both anticipated and realized changes in the skill premium
732 induced by AI.

¹⁵Empirical 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.

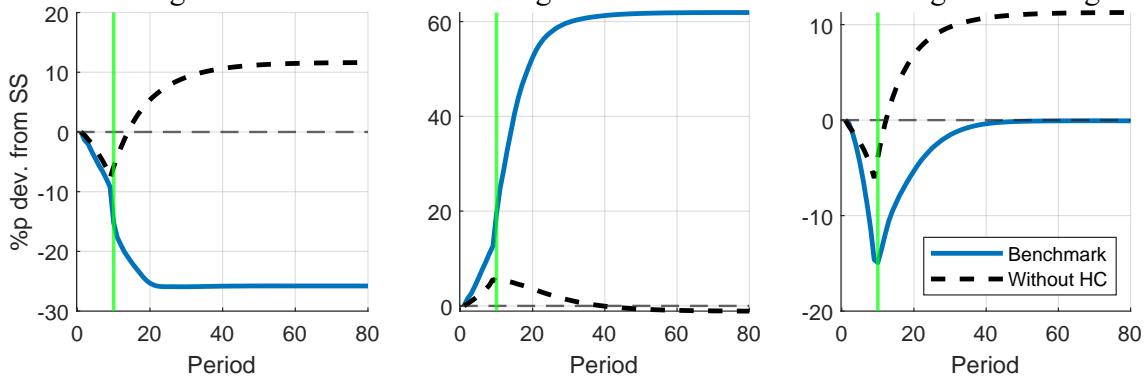
733 6.2.1 Income, earnings, and consumption inequalities

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

737 **AI's direct impacts:** Without any human capital adjustments, AI's impact on
 738 inequalities is primarily driven by productivity gains in the low and high sectors
 739 – 7.5% and 5%, respectively. As a result, there is little direct impact on income
 740 and earnings Gini coefficients in anticipation of AI before period 10. After AI is
 741 implemented, both income and earnings inequality decline: higher labor productivity
 742 raises earnings in the low sector, while wage declines in the middle sector compress
 743 the distribution. Consumption inequality remains largely unchanged throughout
 744 the transition.

745 **Effects of AI-induced human capital adjustments:** Allowing human capital
 746 to adjust endogenously, however, leads to pronounced job polarization, as shown in
 747 Section 5.2. Households who would have qualified for middle-sector jobs now tran-
 748 sition to either the low or high sector. Those moving to the low sector see reduced
 749 labor earnings, while those shifting to the high sector enjoy increased earnings. This
 750 polarization drives up earnings and income inequality, both before and after AI is
 751 implemented. As income disparities widen, consumption inequality also increases.

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.

752 6.2.2 Wealth inequality

753 In stark contrast to the effects on income and earnings inequality, allowing for en-
 754 dogenous human capital adjustment mitigates the negative direct impact of AI on
 755 wealth inequality. While AI’s direct effect would otherwise widen disparities, human
 756 capital responses help dampen the increase in wealth inequality, underscoring the
 757 stabilizing role of human capital adjustments in the wealth distribution.

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

768 In our quantitative model, this mechanism shows up most clearly in the middle
 769 sector. Figure 8 plots the transition of average assets by sector in the benchmark
 770 economy and in the counterfactual No HC economy. “Average Asset” is defined as
 771 total assets held by households in a given sector divided by that sector’s popula-
 772 tion share, so it reflects both within-sector saving behavior and the composition of
 773 households across sectors.

774 **AI’s direct impacts:** Without any human capital adjustment, AI’s impact on
 775 households’ saving works purely through income effect. In both the low and high
 776 sectors, households reduce their savings in anticipation of AI, expecting higher life-

777 time labor income. After AI is implemented at period 10, their savings increase
778 alongside rising labor incomes. In contrast, households in the middle sector, antic-
779 ipating a negative income effect from AI due to a lower wage rate, increase their
780 savings prior to period 10. Once AI is introduced and the wage rate recovers,
781 middle-sector households reduce their savings.

782 **Effects of AI-induced human capital adjustments:** Endogenous human cap-
783 ital responses introduce an additional channel. Relative to the No-HC model, the
784 benchmark exhibits a pronounced increase in average assets in the middle sector.¹⁶
785 Middle-sector households are relatively productive in our model, and a composi-
786 tion effect further amplifies their asset accumulation: many less productive middle-
787 sector households endogenously move down to the low sector, so the remaining
788 middle-sector population is positively selected on productivity.¹⁷ In addition, as
789 discussed above, some middle-sector households voluntarily exit employment to in-
790 vest in human capital full-time. Taken together, these households are the “active
791 training” and relatively high-productivity workers in our model; thus, as predicted
792 by Propositions 2 and 3, their human capital investment tends to crowd in saving.
793 Accordingly, AI-induced human capital adjustment strengthens asset accumulation
794 in the middle of the distribution and compresses the gap between the middle and
795 the top. Quantitatively, the increase in wealth inequality in the benchmark economy
796 with endogenous human capital is therefore markedly smaller than in the No HC
797 economy, highlighting the stabilizing role of human capital adjustment in the wealth
798 distribution.

799 7 Conclusion

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

806 Our work points to several promising directions for future research on the eco-
807 nomic impacts of AI. First, if governments implement redistribution policies to ad-
808 dress AI-induced inequality, understanding how these policies influence human capi-
809 tal accumulation, and thus their effectiveness, would be valuable. Second, our model
810 assumes households have perfect foresight when making human capital investments.

¹⁶In 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.

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

811 Relaxing this assumption could reveal new insights into the economic trajectory of
812 AI advancements and offer important policy implications.

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910 A Household Decision Rule Cutoffs

911 A.1 Additional cutoffs formulae for households

$$\bar{z}_{non}^M(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'}{1+r'}]}{w} \quad (\text{A.1})$$

$$\bar{z}_{slow}^M(a) := \frac{(\exp(\frac{\chi_n - \chi_e e_H}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}] + \lambda \frac{w'z'}{1+r'}}{w} \quad (\text{A.2})$$

$$\bar{z}_{fast}^M(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}]}{w} \quad (\text{A.3})$$

$$\bar{z}_{fast}^M(a) := \frac{\left\{ \lambda \left[\exp(\frac{\chi_e e_L}{1+\beta}) - 1 \right]^{-1} - 1 \right\} \frac{w'z'}{1+r'} - (1+r)a}{w} \quad (\text{A.4})$$

$$\bar{z}_{non}^H(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}]}{w} \quad (\text{A.5})$$

912 *A.2 Parameter restrictions for cutoffs ranking*

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

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

915 or equivalently:

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

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

916 To avoid $(n = 1, e = e_L)$ from being a dominated choice, we need another lower
 917 bound for λ . To see it, recall that $(n = 1, e = 0)$ is better than $(n = 1, e = e_L)$
 918 if $z > \bar{z}_{fast}$, and $(n = 1, e = e_L)$ is better than $(n = 0, e = e_L)$ if $z > \underline{z}_{fast}$.
 919 $(n = 1, e = e_L)$ is therefore the best choice over the interval $(\underline{z}_{fast}, \bar{z}_{fast})$. For such an
 920 interval to exist, it must be the case that when $z = \underline{z}_{fast}$, $\bar{z} < \bar{z}_{fast}$. $z = \underline{z}_{fast}$ means
 921 that the fast learners are indifferent between $(n = 1, e = e_L)$ and $(n = 0, e = e_L)$ so
 922 that

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

932 We can then conclude that the conditions (A.7) and (A.13) are sufficient for
933 1) the slower learners always prefers $(n = 0, e = e_H)$ over $(n = 0, e = 0)$, and 2)
934 $\bar{z}_{fast} > \underline{z}_{fast}$, i.e., there exists state space where $(n = 1, e = e_L)$ is optimal.

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

936 For the fast learners, their cutoffs rank as follows

$$\frac{\bar{z}_{fast}^L(a)}{1 - \lambda} > \bar{z}_{fast}^L(a) > \bar{z}_{fast}^M(a) > \frac{\bar{z}_{fast}^M(a)}{1 + \lambda} \quad (\text{A.14})$$

$$\frac{\underline{z}_{fast}^L(a)}{1 - \lambda} > \underline{z}_{fast}^M(a) > \underline{z}_{fast}^L(a) > \frac{\underline{z}_{fast}^M(a)}{1 + \lambda} \quad (\text{A.15})$$

937 For the slow learners, the rank of their cutoffs is

$$\frac{\bar{z}_{slow}^L(a)}{1 - \lambda} > \bar{z}_{slow}^M(a) > \bar{z}_{slow}^L(a) > \frac{\bar{z}_{slow}^M(a)}{1 + \lambda} \quad (\text{A.16})$$

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

$$\frac{\bar{z}_{non}^L(a)}{1 - \lambda} > \bar{z}_{non}^M(a) > \frac{\bar{z}_{non}^H(a)}{1 + \lambda} > \frac{\bar{z}_{non}^M(a)}{1 + \lambda} \quad (\text{A.17})$$

$$\bar{z}_{non}^M(a) > \bar{z}_{non}^L(a) \quad (\text{A.18})$$

939 **B Proof of Proposition**

940 *B.1 Proof of Proposition 2*

941 The derivative of saving with respect to t is

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

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

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

943 Define

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

944 Then equation (B.2) can be written as

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

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

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

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

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

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

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

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

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

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

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

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

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

955 *B.2 Proof of Lemma 1*

956 Denote

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

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

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

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

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

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

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

$$G(x, a; t) \rightarrow 0 \quad (x \rightarrow 0),$$

961

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

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

963 If

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

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

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

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

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

967 If

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

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

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

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

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

970 *B.3 Proof of Proposition 4*

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

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

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

975 *B.4 Proof of Proposition 5*

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

976 differentiating with respect to t gives

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

977 Since

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

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

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

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

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

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

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

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

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

984 **Case 1:** $1 < t < t'$

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

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

986 Since f is increasing,

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

987 which implies

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

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

989 Now for any $t' > t$,

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

990 and therefore

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

991 We then have that:

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

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

994 **Case 2:** $t < t' < 1$

995 For $t < 1$,

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

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

$$-\int_t^1 f(u) du > 0 \implies \int_t^1 f(u) du < 0.$$

997 Since f is increasing

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

998 which implies

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

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

1000 Consider

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

1001 If $f(u) < 0$ for all $u \in [t, t']$, then $\int_t^{t'} f(u) du < 0$.

1002 If there exists some $t_s \in [t, t']$ such that $f(t_s) = 0$, so $f(u) < 0$ for $u < t_s$ and
1003 $f(u) > 0$ for $u > t_s$. Then $f(u) > 0$ for $u \in [t', 1]$. Hence,

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

1004 This implies that

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

1005 Together with the inequality $\Delta_{\text{on-job}}(x, a; t) > 0$, we have that

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

1006 We then have that

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

1007 Thus, for $t < 1$, whenever $\Delta_{\text{on-job}}(x, a; t) > 0$, increasing t toward 0 makes $\Delta_{\text{on-job}}$
1008 strictly decrease.

1009 C Computational Procedure for the Quantitative Model

1010 C.1 Steady-state Equilibrium

1011 In the steady-state, the measure of households, $\mu(a, h, z)$, and the factor prices are
1012 time-invariant. We find a time-invariant distribution μ . We compute the house-
1013 holds' value functions and the decisions rules, and the time-invariant measure of the
1014 households. We take the following steps:

1015 1. We choose the number of grid for the risk-free asset, a , human capital, h , and
1016 the idiosyncratic labor productivity, z . We set $N_a = 151$, $N_h = 151$, and
1017 $N_z = 9$ where N denotes the number of grid for each variable. To better
1018 incorporate the saving decisions of households near the borrowing constraint,
1019 we assign more points to the lower range of the asset and human capital.

1020 2. Productivity z is equally distributed on the range $[-3\sigma_z/\sqrt{1-\rho_z^2}, \sqrt{1-\rho_z^2}]$. As shown
1021 in the paper, we construct the transition probability matrix $\pi(z'|z)$ of the
1022 idiosyncratic labor productivity.

- 1023 3. Given the values of parameters, we find the value functions for each state
 1024 (a, h, z) . We also obtain the decision rules: savings $a'(a, h, z)$, and $h'(a, h, z)$.
 1025 The computation steps are as follow:
- 1026 4. After obtaining the value functions and the decision rules, we compute the
 1027 time-invariant distribution $\mu(a, h, z)$.
- 1028 5. If the variables of interest are close to the targeted values, we have found the
 1029 steady-state. If not, we choose the new parameters and redo the above steps.

1030 *C.2 Transition Dynamics*

1031 We incorporate the transition path from the status quo to the new steady state. We
 1032 describe the steps below.

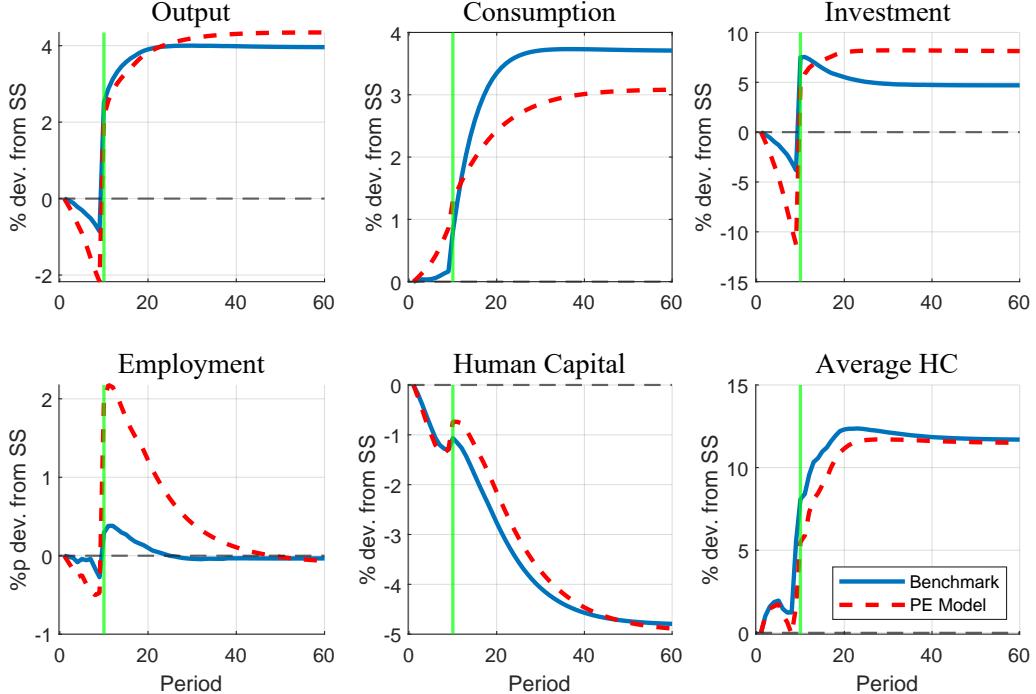
- 1033 1. We obtain the initial steady state and the new steady state.
- 1034 2. We assume that the economy arrives at the new steady state at time T . We
 1035 set the T to 100. The unit of time is a year.
- 1036 3. We initialize the capital-labor ratio $\{K_t/L_t\}_{t=2}^{T-1}$ and obtain the associated
 1037 factor prices $\{r_t, w_t\}_{t=2}^{T-1}$.
- 1038 4. As we know the value functions at time T , we can obtain the value functions
 1039 and the decision rules in the transition path from $t = T - 1$ to 1.
- 1040 5. We compute the measures $\{\mu_t\}_{t=2}^T$ with the measures at the initial steady state
 1041 and the decision rules in the transition path.
- 1042 6. We obtain the aggregate variables in the transition path with the decision rules
 1043 and the distribution measures.
- 1044 7. We compare the assumed paths of capital and the effective labor with the
 1045 updated ones. If the absolute difference between them in each period is close
 1046 enough, we obtain the converged transition path. Otherwise, we assume new
 1047 capital-labor ratio and go back to 3.

1048 **D Investigating the GE channel of AI's impact**

1049 Figures 9 and 10 compare the transition dynamics in the benchmark general-equilibrium
 1050 model with those in a partial-equilibrium (PE) version of the model, where individ-
 1051 ual behavior responds to AI adoption but factor prices are held fixed at their initial
 1052 steady-state values. The green vertical line marks the date of AI adoption.

1053 On the aggregate side (Figure 9), both models deliver a long-run expansion in
 1054 output, consumption, and investment after AI adoption. In the PE model, GDP

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

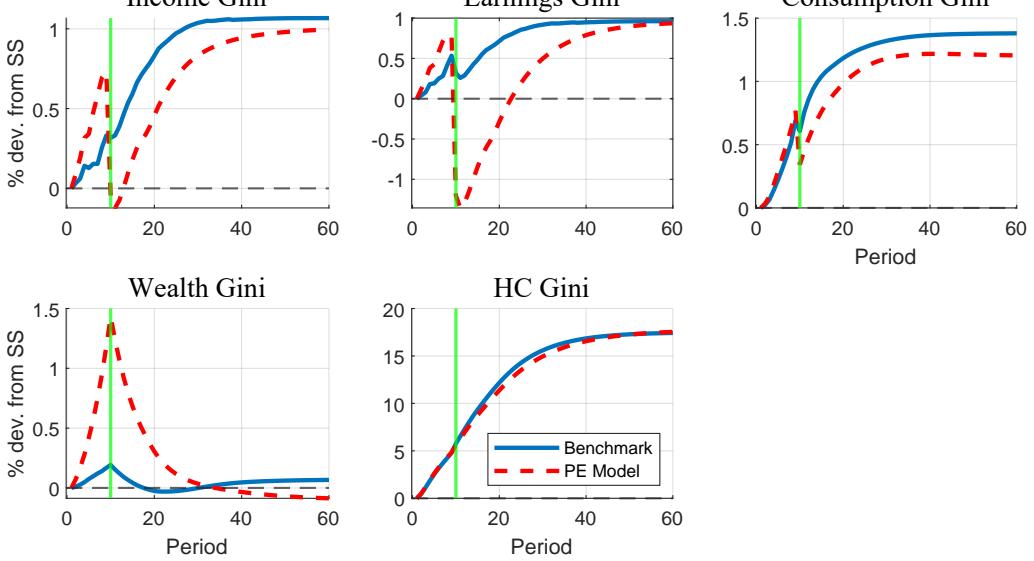


Note: The transition paths of aggregate variables: benchmark vs. PE models. The x-axis represents years, and the y-axis shows the percentage deviation from the initial steady state. AI introduction is assumed to occur in period 10. The PE model is an economy in which factor prices are held fixed at their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

1055 responses are quite similar across the two models, but the composition of that re-
 1056 sponse differs. In the PE model, consumption rises by less, while investment rises
 1057 by more in the long run. The reason is that, in the benchmark, the long-run re-
 1058 turn on capital becomes negative (as shown in Figure 6), whereas in the PE model
 1059 there is no such price effect. As a result, households in the PE environment have
 1060 stronger incentives to save and invest, tilting the response toward investment rather
 1061 than consumption. Even though aggregate human-capital dynamics do not differ
 1062 much across the two environments, employment behaves very differently around the
 1063 adoption date. In the PE model, employment rises sharply when AI is introduced
 1064 because wages do not fall as employment increases.

1065 Turning to inequality dynamics (Figure 10), the long-run behavior is similar
 1066 across the two environments, but the impact responses differ markedly. As noted
 1067 above, employment rises more on impact in the PE model even though output re-
 1068 sponses are similar. This implies that the additional employment mainly comes from
 1069 low-productivity households. Consequently, the Gini coefficients for income, earn-
 1070 ings, and consumption fall more on impact in the PE model but then move toward
 1071 levels similar to those in the benchmark once job polarization and skill reallocation
 1072 take hold. The human-capital Gini shows virtually no difference between the two
 1073 models. By contrast, the wealth Gini exhibits very different transition dynamics.
 1074 In the PE model, it displays a pronounced but short-lived spike early in the transi-
 1075 tion because poor households save less, as wages do not fall there in response to AI

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.

1076 adoption, unlike in the benchmark economy. In the long run, however, the wealth
 1077 Gini converges to a level similar to the benchmark, mainly because middle-sector
 1078 households gradually increase their savings, as discussed in the main text.