

AI and Human Capital Accumulation: Aggregate and Distributional Implications*

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Abstract

This paper develops a model to analyze the effects of AI advancements on human capital investment and their impact on aggregate and distributional outcomes in the economy. We construct an incomplete markets economy with endogenous asset accumulation and general equilibrium, where households decide on human capital investment and labor supply. Anticipating near-term AI advancements that will alter skill premiums, we analyze the transition dynamics toward a new steady state. Our findings reveal that human capital responses to AI amplify its positive effects on aggregate output and consumption, mitigate the AI-induced rise in precautionary savings, and stabilize the adjustments in wages and asset returns. Furthermore, while AI-driven human capital adjustments increase inequalities in income, earnings, and consumption, they unexpectedly reduce wealth inequality.

Keywords: AI, Job Polarization, Human Capital, Inequality

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1 Introduction

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

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

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

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

In anticipation of these changes, households are likely to adjust their human capital investments. A 2022 report by Higher Education Strategy Associates finds that following decades of growth, dropping student enrollment has become a major

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.

38 trend in higher education in the Global North (Higher Education Strategy Asso-
39 ciates, 2022). In the U.S., the public across the political spectrum has increasingly
40 lost confidence in the economic benefits of a college degree.²

41 This paper develops a model to study the effects of AI advancements on human
42 capital investment and their subsequent impact on aggregate and distributional
43 outcomes of the economy. We posit an economy consisting of three sectors, requiring
44 low, middle and high levels of skill (human capital) with increasing sectoral labor
45 productivity. Households can invest in their human capital to move up to more
46 productive sectors. But if they do not invest, their human capital depreciates and,
47 over time, they will move down to less productive sectors. We model human capital
48 investment at two levels, a low level attainable on the job and a high level requiring
49 full-time commitment, such as pursuing higher education. Households are subject
50 to uninsurable idiosyncratic risk in terms of productivity shocks that affect both
51 labor productivity and effectiveness in human capital investment.

52 The interaction between human capital investment and labor supply presents a
53 tradeoff at the household level between current wage earning and future wage gains.
54 At aggregate level, the interaction implies that when individuals transition from
55 the middle to the high sector, they may temporarily exit the workforce to upskill,
56 reducing immediate labor supply but improving future labor productivity.

57 Add interaction between human capital and saving.

58 We model AI advancements as increasing the productivity for the low and high
59 sectors but not for the middle sector so that the skill premium of the middle sector
60 decreases and the skill premium of the high sector increases. Allowing for human
61 capital adjustments not only alters AI's economic implications quantitatively, it also
62 makes a qualitative difference.

63 If the skill distribution is fixed, AI will unambiguously improve the labor pro-
64 ductivity of the whole economy. However, allowing human capital to adjust enables
65 workers to upskill or downskill. The response of overall labor productivity could be
66 enhanced, or dampened, or even reverted depending on whether workers move to
67 more or less productive sectors.

68 Using a two-period model, we show how households' labor supply and human
69 capital investment are affected by their productivity shocks, asset holdings and
70 stocks of human capital. The effects of AI, in this partial equilibrium analysis, are
71 shown to discourage human capital investment for households in the low sector and
72 encourage human capital investment for households in the middle sector, thereby
73 increasing human capital inequality. In addition, AI worsens consumption inequality
74 for households with low levels of human capital and reduces consumption inequality

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 (Public Agenda, 2022), a nonpartisan research organization, shows that young Americans without college degrees are most skeptical about the value of higher education.

75 for those with high levels of human capital.

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

86 We find that aggregate human capital rises sharply even before AI introduction,
87 indicating that a substantial portion of workers, anticipating changes in skill pre-
88 mium, leave the labor force early to accumulate human capital. The economy also
89 experiences AI-induced job polarization, with a notable reallocation of workers from
90 the middle sector to either low or high sectors.

91 Building on these labor dynamics, our model examines how AI influences both
92 the aggregate and distributional outcomes of the economy, including output, con-
93 sumption, investment, employment, income inequality, consumption inequality, and
94 wealth inequality. Our focus is on how human capital adjustments reshape AI's
95 effects on each of these outcomes. Specifically, we examine two primary chan-
96 nels through which human capital adjustments operate: the redistribution channel,
97 which reallocates workers across skill sectors, and the general equilibrium channel,
98 which operates through wages and capital return changes.

99 Our findings reveal that human capital responses to AI amplify its positive effects
100 on aggregate output and consumption, mitigate the AI-induced rise in precautionary
101 savings, and stabilize the adjustments in wages and asset returns. Furthermore,
102 while AI-driven human capital adjustments increase inequalities in income, earnings,
103 and consumption, they unexpectedly reduce wealth inequality. We also show that
104 the redistribution channel is the dominant factor in the effects of human capital
105 adjustments, whereas the general equilibrium channel, via wage and capital return
106 changes, plays a comparatively minor role.

107 INTRODUCING PRECAUTIONARY SAVING MOTIVE IN THE WAGE PO-
108 LARIZATION INVESTIGATION Autor *et al.*, (2006) Autor and Dorn (2013)

109 1.1 *Related Literature*

110 This paper relates to the literature examining how technological advancements, in-
111 cluding AI, have significantly contributed to job polarization. Goos and Manning
112 (2007) show that since 1975, the United Kingdom has experienced job polarization,
113 with increasing employment shares in both high- and low-wage occupations. Autor

114 and Dorn (2013) expanded on this by providing a unified analysis of the growth of
115 low-skill service occupations, highlighting key factors that amplify polarization in
116 the U.S. labor market. Empirical evidence from Goos *et al.*, (2014) further confirms
117 pervasive job polarization across 16 advanced Western European economies. In the
118 U.S., Acemoglu and Restrepo (2020) show that robots can reduce employment and
119 wages, finding robust negative effects of automation on both in various commuting
120 zones.

121 The introduction of AI and robotics has had adverse effects on labor markets,
122 with significant implications for employment and labor force participation. Lerch
123 (2021) highlights that the increasing use of robots not only displaces workers but
124 also negatively impacts overall labor force participation rates. Similarly, Faber *et al.*,
125 (2022) demonstrate that the detrimental effects of robots on the labor market have
126 resulted in a decline in job opportunities, particularly in sectors where automation
127 is prevalent. These findings suggest that while technological advancements bring
128 productivity gains, they simultaneously reduce employment prospects and partici-
129 pation in the labor market, exacerbating economic challenges for certain groups of
130 workers.

131 The introduction of AI and robotics also influences human capital accumulation
132 as workers respond to technological disruption. Faced with the employment risks
133 brought about by automation, many exposed workers may invest in additional ed-
134 ucation as a form of self-insurance, rather than relying on increases in the college
135 wage premium (Atkin, 2016; Beaudry *et al.*, 2016). Empirical evidence supports this
136 response. Di Giacomo and Lerch (2023) find that for every additional robot adopted
137 in U.S. local labor markets between 1993 and 2007, four individuals enrolled in col-
138 lege, particularly in community colleges, indicating a rise in educational investments
139 triggered by automation. Similarly, Dauth *et al.*, (2021) show that within German
140 firms, robot adoption has led to an increase in the share of college-educated workers,
141 as firms prioritize higher-skilled employees over those with apprenticeships.

142 The response of human capital accumulation to technological disruption could
143 also go to the other extreme.

144 The rise of AI and automation also plays a significant role in exacerbating gen-
145 eral inequality, particularly through its impact on education and wealth distribution.
146 Prettnner and Strulik (2020) present a model showing that innovation-driven growth
147 leads to an increasing proportion of college graduates, which in turn drives higher
148 income and wealth inequality. As technology advances, workers with higher educa-
149 tional attainment benefit disproportionately, widening the gap between those with
150 and without advanced skills. Sachs and Kotlikoff (2012) also explore this dynamic,
151 providing a model within an overlapping generations framework that examines the
152 interaction between automation and education. They demonstrate how automation
153 can further entrench inequality by favoring workers with higher levels of educa-

tion, as those without adequate skills are more likely to be displaced or see their wages stagnate. This interaction between technological change and educational attainment not only amplifies economic inequality but also perpetuates disparities in wealth across generations.

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

2 Model Environment

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

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

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

2.1 Production Technology

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

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

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

These sectors differ in their technologies for converting labor into effective labor units and in the levels of human capital required for employment. The middle sector employs households with human capital above h_M and converts one unit of labor to one effective labor unit. The high sector, requiring human capital above h_H , converts one unit of labor to $1 + \lambda$ effective units, while the low sector, with no

186 human capital requirement, converts one unit into $1 - \lambda$ effective units. This implies
 187 a sectoral labor productivity $x(h)$ that is a step function in human capital:

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

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

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

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

193 2.2 Household's Problem

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

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

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

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

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

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

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

204 Human capital investment can take three levels of effort: $\{0, e_L, e_H\}$. A non-
 205 working household is free to choose any of the three effort levels but a working
 206 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.

207 working and human capital investment. Hence:

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

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

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

209 where δ is human capital's depreciation rate.

210 3 Household Decisions in a Two-Period Model

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

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

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

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

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

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

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

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

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

227 To see the implication of this trade-off and how it interacts with uninsured
228 idiosyncratic risk, we proceed in two steps. We first derive the period-1 decisions
229 without uncertainty by assuming that z' is known to the household at period 1 and

230 z' is such that the household will work in period 2. We then reintroduce uncertainty
 231 in z' and compare the decision rules with the case without uncertainty.

232 3.1 Period-1 Labor Supply and Human Capital Investment

233 3.1.1 Consumption and saving without uncertainty

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

$$c + \frac{c'}{1+r'} = (1+r)a + n(wzx(h)) + \frac{w'z'x(h')}{1+r'}$$

with $h' = ze + (1-\delta)h$.

237 The log utility in consumption implies the optimality condition:

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

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

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

240 3.1.2 Labor supply and human capital investment

241 The optimal consumption rules in (14) and (13) allow us to express the household's
 242 problem as the maximization of an objective function in labor supply n and human
 243 capital investment e :⁴

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

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

248 We now derive the decision rules for households $h \in [h_M, h_M(1-\delta)^{-1})$ in detail,
 249 as the decision rules for the other four ranges are similar. For households with
 250 $h < h_M(1-\delta)^{-1}$, we define two cutoffs in z :

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

⁴This follows since $c' = \beta(1+r')c$, so $\ln c' = \ln \beta + \ln(1+r') + \ln c$.

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

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

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

257 **Slow learners** are households with $z \in (\underline{z}_M(h), \bar{z}_M(h))$. These households can
 258 reach $h' > h_M$ in the next period only by investing $e = e_H$ today. Their choice
 259 is restricted to $e = 0$ or $e = e_H$, since selecting $e = e_L$ incurs a cost without any
 260 future benefit. Slow learners must trade off between working and human capital
 261 investment: choosing $e = e_H$ requires not working today ($n = 0$), while opting to
 262 work means forgoing investment in human capital ($n = 1, e = 0$).⁵

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

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

264 **Fast learners** are households with $z > \bar{z}_M(h)$. They can achieve $h' > h_M$ in
 265 the next period if they invest $e = e_L$ today. In this case, there is no need to exert
 266 high effort e_H in human capital investment. The fast learners choose among three
 267 options: $(n = 1, e = 0)$, $(n = 1, e = e_L)$, and $(n = 0, e = e_L)$.⁶

268 The decision rule for fast learners are as follows:

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

269 where

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

⁵The 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 .

⁶Similar 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 $(n = 0, e = 0)$.

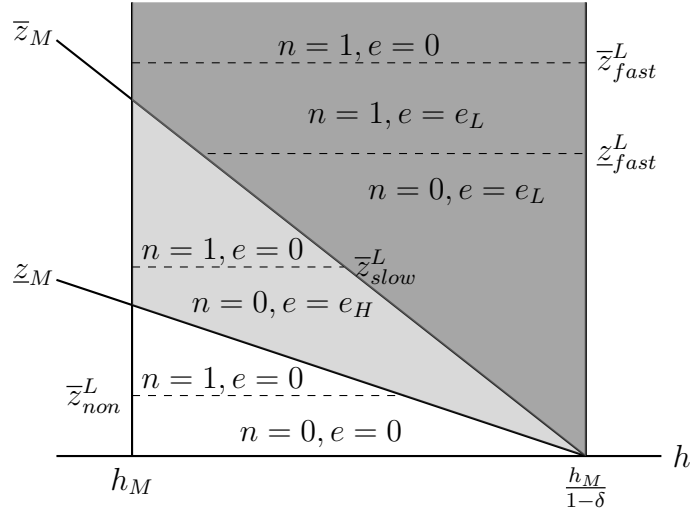


Figure 1: Decision Rule Diagram for $h_M \leq h < h_M(1 - \delta)^{-1}$

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 \underline{z}_{fast}^L that are functions of capital holding a .

270

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

271 We set up our model so that $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.⁷

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

281 This decision rule diagram is representative for households in other four ranges
 282 of human capital. Figure 2 illustrates the regions in which households make positive
 283 human capital investments. Striped shading highlights where investment occurs,
 284 with dark areas denoting fast learners and light areas representing slow learners.

285 For households with $h < h_M$, $\bar{z}_M(h)$ and $\underline{z}_M(h)$ continue to be the boundaries

⁷Appendix 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 $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.

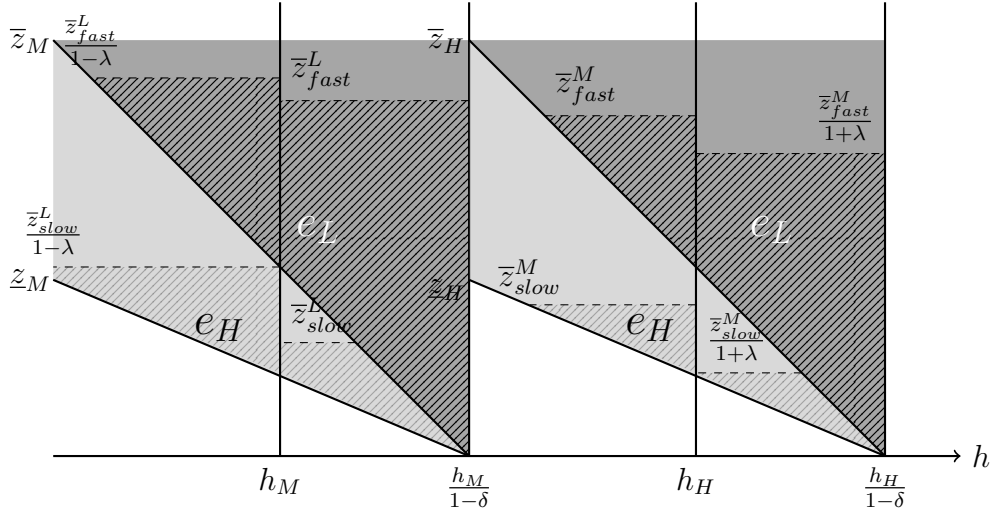


Figure 2: State Space for Human Capital Investment

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.

that separate non-learners, slow learners and fast learners, but the four cutoffs are $\bar{z}_{non}^L \frac{1}{1-\lambda}$, $\bar{z}_{slow}^L \frac{1}{1-\lambda}$, $\bar{z}_{fast}^L \frac{1}{1-\lambda}$, 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 $\bar{z}_{non}^M(a)$, $\bar{z}_{slow}^M(a)$, $\bar{z}_{fast}^M(a)$, and $\bar{z}_{fast}^M(a)$ (see Appendix A.1 for the explicit formulae).⁸ If $h_H \leq h < h_H \frac{1}{1-\delta}$, the analogous cutoffs are given by $\bar{z}_{non}^M \frac{1}{1+\lambda}$, $\bar{z}_{slow}^M \frac{1}{1+\lambda}$, $\bar{z}_{fast}^M \frac{1}{1+\lambda}$, 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 .

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

⁸Appendix A.2 provides parameter restrictions for $\bar{z}_{fast}^M(a) > \bar{z}_{fast}^M(a)$.

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

From the perspective of human capital investment, the uncertain z' is associated with risk in the return to human capital. Conditional on working, households' income increases with z' : $c' = (1 + r')a' + w'x(h')z'$. $\ln(c')$ is increasing and concave in z' , and a higher $x(h')$ increases the concavity.⁹ Consider two levels of h' , $\bar{h}' > \underline{h}'$, a mean-preserving spread of z' distribution reduces the expected utility at both levels of h' but the reduction is larger for the higher level \bar{h}' . Hence, the expected utility gain of moving from \underline{h}' to \bar{h}' is smaller due to the idiosyncratic risk. Human capital investment is discouraged.

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

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

3.3 Period-1 Saving and Human Capital Investment

In this section, we study the impact of endogenous human capital investment on households' saving decisions. Specifically, we compare optimal saving behavior in two scenarios: one in which households can choose to invest in human capital, and an alternative scenario in which human capital is exogenously fixed. To facilitate the comparison, we assume in this section that there is no human capital depreciation.¹⁰

When the optimal choice of human capital investment is zero, optimal saving is identical in both scenarios. When the optimal human capital investment is either e_L

⁹The 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.

¹⁰If depreciation is allowed, the analysis proceeds similarly but involves more comparison paris.

or e_H , we compare the household's optimal saving to the case where human capital investment is exogenously fixed at zero, i.e., $(n = 1, e = 0)$.¹¹

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

In particular, the household maximizes expected lifetime utility:

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

subject to the budget constraints

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

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

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

3.3.1 Effect of on-job-training on saving

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

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

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

where $t \geq 1$ represents the effect of human capital investment on period-2 income: $t > 1$ if $e = e_L$; $t = 1$ if $e = 0$.

The optimal saving is determined by the FOC:

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

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

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

¹¹Why 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.

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

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

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 $t^2x^2\Sigma$ 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 skill, so that the overall impact of on-job-training on saving can differ between low-
 373 and high-skilled households.

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

income in period 1, which is not the case for on-job-training. Following the same normalization and notation as in the previous subsection, we can write the budget constraints with full-time training and without training as:

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

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

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

The second-order approximate solution to the optimization problem is:

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

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

so that the total effect of full-time training on saving is:

$$\Delta_{\text{full-time}}(x, a; t) = a'_{e_H}^*(x, a; t) - a'^*(x, a; 1) \quad (37)$$

$$= \Delta_{\text{on-job}}(x, a; t) - x \frac{\beta}{1 + \beta} + \frac{t^2 x^2 \Sigma}{\beta} \frac{x}{(a + x + tx\mu)(a + tx\mu)} \quad (38)$$

Compared to the effect of on-job-training, represented by $\Delta_{\text{on-job}}(x, a; t)$ defined in (32), full-time training introduces two additional effects on saving. First, it further reduces saving because households forgo their period-1 labor income, as reflected in the second term. Second, it increases precautionary saving, since having lower current resources leaves households less able to self-insure against idiosyncratic risk in period 2, which is captured by the third term. Denote the net additional effect of full-time training on saving as:

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

so that $\Delta_{\text{full-time}}(x, a; t) = \Delta_{\text{on-job}}(x, a; t) + \Delta_H(x, a; t)$. The next proposition shows that the net additional effect is negative and stronger for higher skilled households.

Proposition 3. *When the idiosyncratic shock is not too large, i.e., $\frac{\Sigma}{\mu} < \bar{\sigma}(t)$, full-time training crowds out more saving than on-job-training, $\Delta_H(x, a; t) < 0$. Moreover, the crowding-out effect is stronger for higher skilled households: $\Delta_H(x, a; t)$ is decreasing in x .*

Proof. See Appendix B. □

3.4 The Effects of an Anticipated Period-2 AI Shock

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

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

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

3.4.1 Effects on human capital investment

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

Proposition 4. *An anticipated AI shock decreases human capital investment among households with $h < h_M/(1 - \delta)$, but increases it among those with $h > h_M/(1 - \delta)$. Specifically, \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 .*

Proof. See Appendix B. □

3.4.2 Effects on labor supply

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

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

432 3.4.3 Effects on saving

433 The AI shock increases sectoral labor productivities for the low and high sectors in
 434 period 2, while leaving the middle sector's labor productivity unchanged. Its effect
 435 on saving can be analyzed as if we are varying the parameter t in the functions
 436 $\Delta_{\text{on-job}}(x, a; t)$, defined in (32), and $\Delta_H(x, a; t)$, defined in (39).

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

- 438 • 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 $t' > t > 1$.
- 439 • 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 $1 > t' > t$.

440 *Proof.* See Appendix B. □

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

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

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

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

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

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

466 For the middle-sector households who upskill via full-time training, there is an
 467 *additional positive effect* of the AI shock on their saving, because a higher x' increases
 468 $\Delta_H(x, a; t)$ (Proposition 5).

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

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

479 3.5 *Limitations of the two-period model*

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

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

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

500 4 A Quantitative Model

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

Table I: Parameters for the Calibration

Parameter	Value	Description	Target or Reference
β	0.91795	Time discount factor	Annual interest rate
ρ_z	0.94	Persistence of z shocks	See text
σ_z	0.287	Standard deviation of z shocks	Earnings Gini
\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	Income Gini
α	0.36	Capital income share	Standard value
δ	0.1	Capital depreciation rate	Standard value

504 4.1 Calibration

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

509 The time discount factor, β , is calibrated to match an annual interest rate of 4
510 percent. We set χ_n to replicate an 80 percent employment rate. We calibrate χ_e to
511 match the fact that around 30 percent of the population invests in human capital.
512 The borrowing limit, \underline{a} , is set to 0.

513 We calibrate parameters regarding labor productivity process as follows. We
514 assume that x follows the AR(1) process in logs: $\log z' = \rho_z \log z + \epsilon_z$, where
515 $\epsilon_z \sim N(0, \sigma_z^2)$. The shock process is discretized using the Tauchen (1986) method,
516 resulting in a transition probability matrix with 9 grids. The persistence parameter
517 $\rho_z = 0.94$ is chosen based on estimates from the literature. The standard deviation
518 σ_z , is chosen to match the earnings Gini coefficient of 0.63.

519 We deviate from the two-period model by assuming that the labor supply is a
520 discrete choice between 0 and $\bar{n} = 1/3$. This change only rescales the two-period
521 model without altering the trade-off facing the households. But such rescaling facil-
522 itates the interpretation that households are deciding whether to allocate one-third
523 of their fixed time endowment to work. The high-level human capital accumulation
524 effort, e_H is assumed to equal \bar{n} . The low-level effort, e_L is set to half of e_H . The skill
525 premium across sectors, λ , is set at 0.2 to match the income Gini coefficient. Human
526 capital cutoffs, h_M and h_H , are set so that the population shares in low, middle, and
527 high sectors are, respectively, 20, 40, and 40 percent. This population distribution

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

roughly matches the fractions of U.S. workers in 2014 who are employed in routine manual occupations (low sector), routine cognitive and non-routine manual (middle sector), and non-routine cognitive (high sector) (Cortes *et al.*, 2017).

On the production side, we set the capital income share, α , to 0.36, and the depreciation rate, δ , to 0.1.

4.2 Key Moments: Data vs. Model

In Table II, we present a comparison of key moments between the model and the empirical data. The model does an excellent job of replicating the 80% employment rate observed in the data. In this context, employment is defined as having positive labor income in the given year, consistent with the common approach used in the literature. According to OECD (1998), the share of the population investing in human capital—those who are actively engaged in skill acquisition or education—is approximately 30%, a figure well matched by the model’s predictions. This is an important metric because it reflects the model’s capacity to capture the dynamics of human capital formation, which plays a critical role in shaping long-run earnings and income inequality. Additionally, the model accurately captures the distribution of income and earnings, aligning closely with observed data. This suggests that the model effectively incorporates the key mechanisms driving labor market outcomes and the corresponding distributional aspects of earnings. Although the model does not explicitly target the wealth Gini coefficient, it achieves a close match to the data: the empirical wealth Gini is 0.78, while the model produces a value of 0.76. This highlights the model’s ability to capture substantial wealth inequality in the economy.

4.3 Steady-state Distribution

Table III presents the steady-state distribution of population, employment, and assets across sectors. The population shares are calibrated to 20%, 40%, and 40% by adjusting the human capital thresholds that define sectors. The shares of employment and assets are endogenously determined by households’ labor supply and savings decisions. Notably, the high sector accounts for 46% of total employment—exceeding its population share—indicating that a disproportionate number

Figure 3: Steady-state Human Capital Distribution

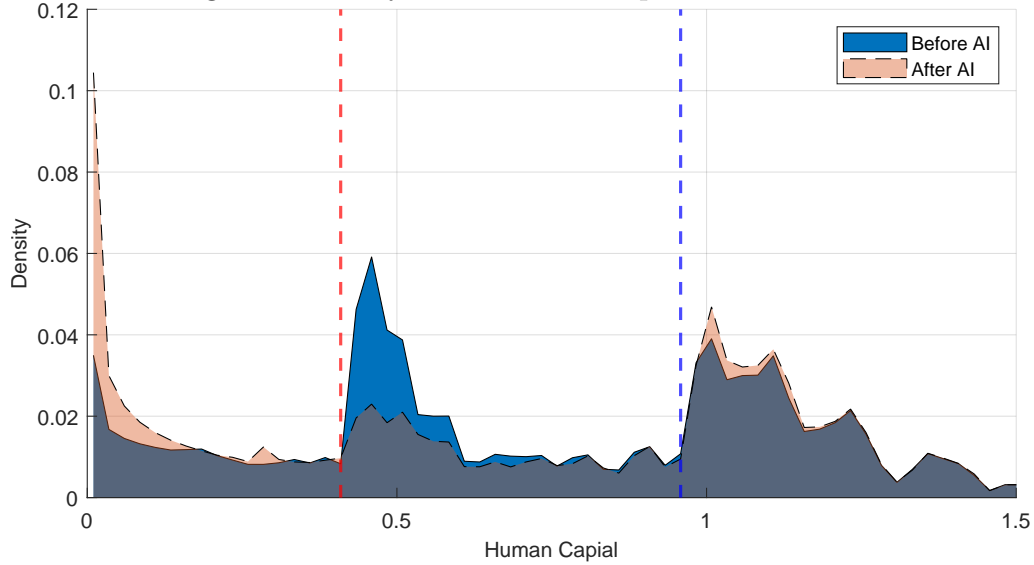
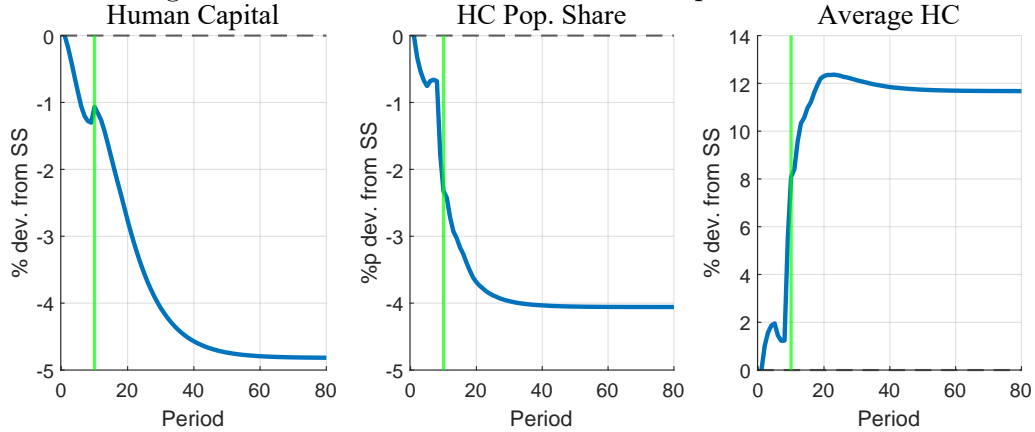


Figure 4: Transition Path for Human Capital Investment



558 of households choose to work in that sector. Asset holdings are even more skewed:
 559 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.

560 5 AI's Impact on Human Capital Adjustments

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

565 adjusts in anticipation of, and in response to, the adoption of AI.

566 The effect of AI on the sectorial productivity is modeled as in (40) with $\gamma = 0.3$.
567 That is, AI boosted the productivity of the low sector workers by 7.5% and the
568 productivity of the high sector workers by 5%, leaving the middle sector intact.
569 It captures the key idea that AI increases average labor productivity (Acemoglu
570 and Restrepo, 2019), but reduces the earning premium for the middle sector, and
571 enlarges the earning premium for the higher sector relative the middle sector.

572 5.1 *Human Capital Adjustments*

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

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

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

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

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

600 Additionally, human capital accumulation becomes increasingly concentrated
601 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.¹²

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.

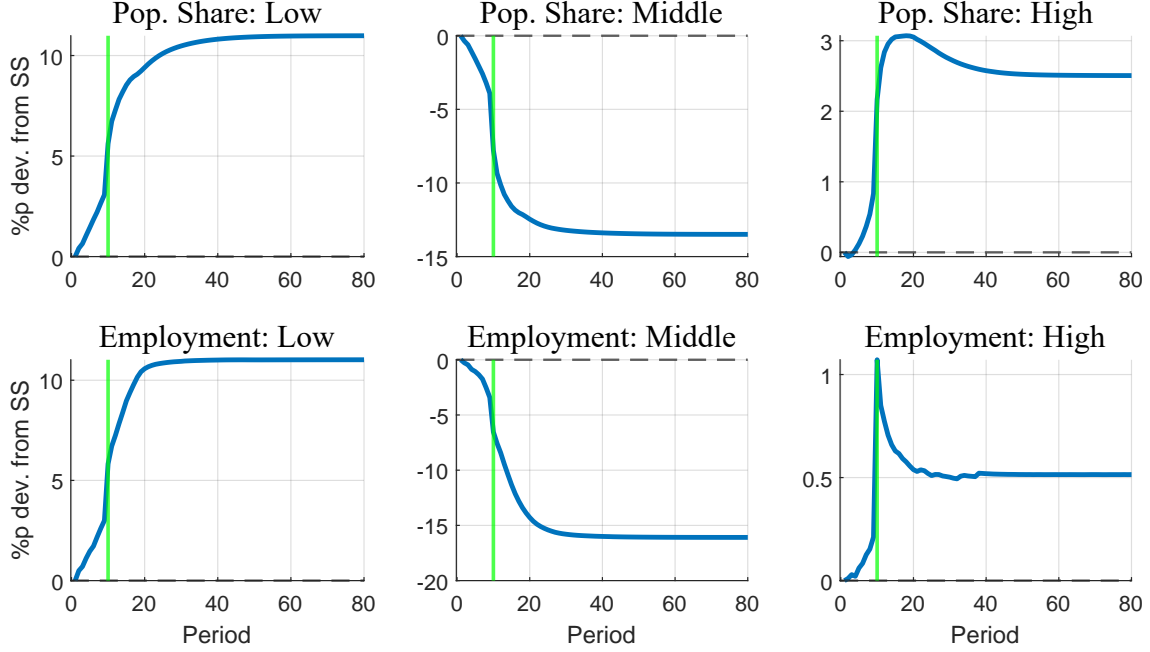
Voluntary job polarization This worker reallocation aligns with the phenomenon of “job polarization” (Goos *et al.*, 2014), where AI and automation technologies disproportionately replace tasks commonly performed by middle-skilled workers. However, our model introduces a complementary mechanism to the conventional understanding of this reallocation. Specifically, households in our model voluntarily exit the middle sector even before AI implementation by adjusting their human capital investments – many middle-sector workers opt for non-employment to invest in skills that will better position them for the post-AI labor market. To emphasize this key difference, our model deliberately abstracts from any direct negative effect of AI on middle-sector workers.

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

This disparity arises from two key factors. First, AI enhances the productivity of low-sector workers by 7.5% and high-sector workers by 5%. However, this productivity differential alone does not fully account for the significant asymmetry. The second factor is the variation in labor supply elasticity across sectors. Compared to the high sector, the low sector exhibits higher labor supply elasticity, meaning that the same change in labor earnings triggers larger labor supply responses. This is

¹²The only exception to those patterns occurs at period 10 when the positive effects of AI on sectoral productivity are realized.

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.

because households in the low sector have lower consumption levels, making their marginal utility of consumption more sensitive to changes in their budget. Consequently, a greater proportion of households in the low sector are at the margin between employment and non-employment (Chang and Kim, 2006).

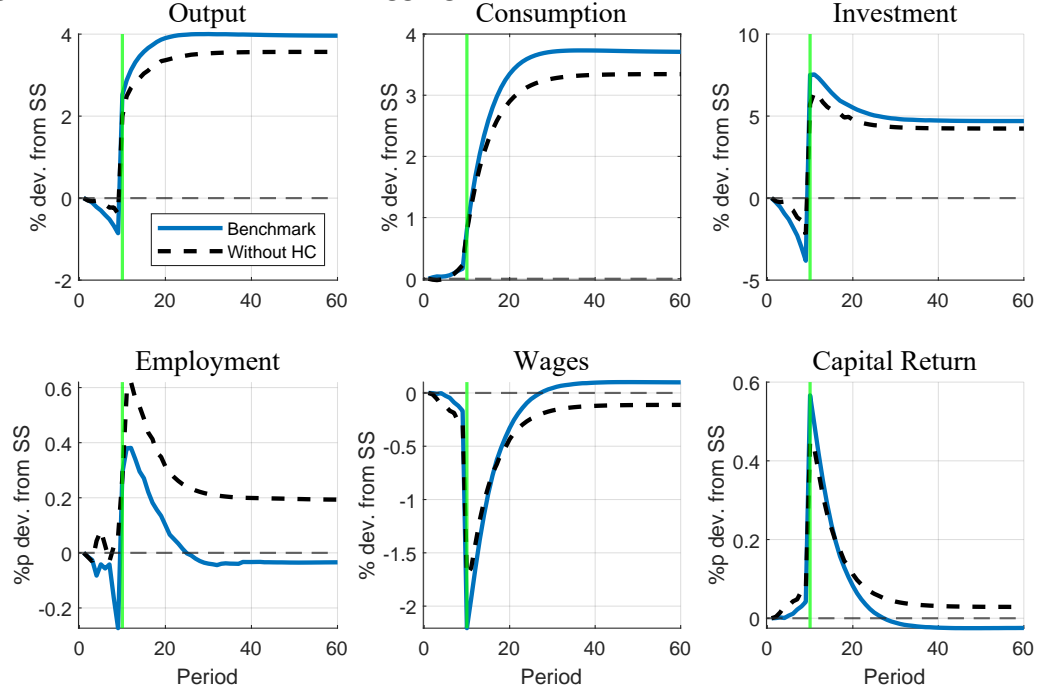
6 The Aggregate and Distributional Effects of AI

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

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

In this section, we examine the importance of endogenous human capital adjustment in shaping both the transitional and long-run effects of AI. To do so, we compare the benchmark economy – where households endogenously adjust their hu-

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.

man capital – with an alternative scenario in which households are held fixed at their initial steady-state human capital during the AI transition (“No HC model”). In both cases, households make endogenous decisions about consumption, savings, and labor supply.

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

6.1 Aggregate Implications

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

6.1.1 AI's direct impacts

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

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

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

6.1.2 AI's indirect impacts via endogenous human capital adjustments

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

In anticipation of AI, employment declines as some households temporarily exit the labor market to invest in human capital and prepare for the post-AI economy.¹³ During this period, labor productivity remains unchanged, so the decline in employment directly translates to a reduction in output. Consistent with standard consumption-smoothing behavior, this reduction is mainly absorbed by lower investment. Meanwhile, the drop in employment mitigates the direct effects of AI on both wages and capital returns prior to the AI implementation.

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

¹³Empirical studies, such as Lerch (2021) and Faber *et al.*, (2022), support the short-term adverse effects of AI adoption on labor markets.

712 more labor to the low and high sectors, thereby better capturing the productivity
713 gains from AI.

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

718 6.2 *Distributional Implications*

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

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

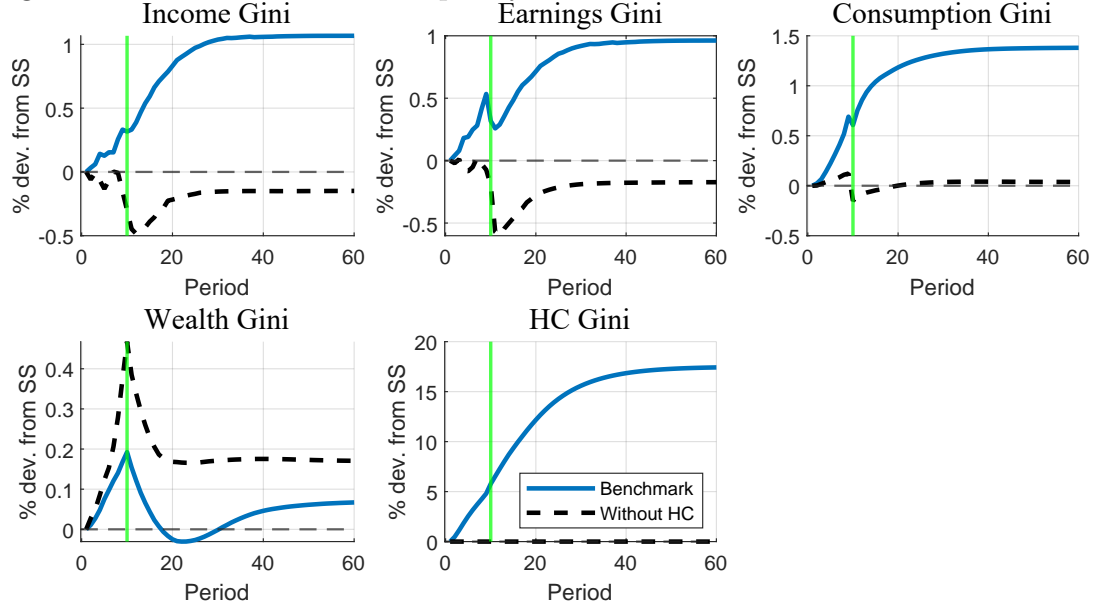
730 6.2.1 **Income, earnings, and consumption inequalities**

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

734 **AI's direct impacts:** Without any human capital adjustments, AI's impact on
735 inequalities is primarily driven by productivity gains in the low and high sectors
736 – 7.5% and 5%, respectively. As a result, there is little direct impact on income
737 and earnings Gini coefficients in anticipation of AI before period 10. After AI is
738 implemented, both income and earnings inequality decline: higher labor productivity
739 raises earnings in the low sector, while wage declines in the middle sector compress
740 the distribution. Consumption inequality remains largely unchanged throughout
741 the transition.

742 **Effects of AI-induced human capital adjustments:** Allowing human capital
743 to adjust endogenously, however, leads to pronounced job polarization, as shown in
744 Section 5.2. Households who would have qualified for middle-sector jobs now tran-
745 sition to either the low or high sector. Those moving to the low sector see reduced
746 labor earnings, while those shifting to the high sector enjoy increased earnings. This

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.

747 polarization drives up earnings and income inequality, both before and after AI is
748 implemented. As income disparities widen, consumption inequality also increases.

749 6.2.2 Wealth inequality

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

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

763 These shifts in sectoral saving patterns sharply increase wealth inequality before
764 period 10, as low-sector households – typically the least wealthy – reduce their asset
765 holdings. After AI is implemented and saving rates in the low sector recover, the
766 wealth Gini coefficient declines from its peak and stabilizes at a level about 0.2%
767 higher than its initial steady state.

768 **Effects of AI-induced human capital adjustments:** Endogenous human cap-
769 ital responses introduce an additional channel. AI-induced changes in the skill
770 premium motivate more households in the middle and high sectors to undertake
771 full-time training, either to move into or remain in the high sector. This extensive
772 margin adjustment requires these households to forgo labor income and rely on their
773 assets to finance consumption, thus reducing their ability to accumulate additional
774 savings during the transition. Meanwhile, low-sector households reduce their full-
775 time investment in human capital, freeing up resources to save more. As a result,
776 this endogenous response of human capital dampens the rise in wealth inequality
777 that would otherwise occur, helping to stabilize the wealth distribution even as AI
778 reshapes the labor market.

779 I cannot really explain well why the wealth gini in the benchmark model is lower
780 than in the No-HC-model, please help to improve this part.

781 7 Conclusion

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

788 Our work points to several promising directions for future research on the eco-
789 nomic impacts of AI. First, while general equilibrium effects—such as wage and
790 capital return adjustments—have a limited role in our model, further research could
791 examine how these effects might vary under different economic conditions or policy
792 environments. Second, if governments implement redistribution policies to address
793 AI-induced inequality, understanding how these policies influence human capital
794 accumulation, and thus their effectiveness, would be valuable. Finally, our model
795 assumes households have perfect foresight when making human capital investments.
796 Relaxing this assumption could reveal new insights into the economic trajectory of
797 AI advancements and offer important policy implications.

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A Household Decision Rule Cutoffs

A.1 Additional cutoffs formulae for households

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

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

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

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

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

A.2 Parameter restrictions for cutoffs ranking

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

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

902 or equivalently:

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

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

903 To avoid $(n = 1, e = e_L)$ from being a dominated choice, we need another lower
 904 bound for λ . To see it, recall that $(n = 1, e = 0)$ is better than $(n = 1, e = e_L)$
 905 if $z > \bar{z}_{fast}$, and $(n = 1, e = e_L)$ is better than $(n = 0, e = e_L)$ if $z > \underline{z}_{fast}$.
 906 $(n = 1, e = e_L)$ is therefore the best choice over the interval $(\underline{z}_{fast}, \bar{z}_{fast})$. For such an
 907 interval to exist, it must be the case that when $z = \underline{z}_{fast}$, $z < \bar{z}_{fast}$. $z = \underline{z}_{fast}$ means
 908 that the fast learners are indifferent between $(n = 1, e = e_L)$ and $(n = 0, e = e_L)$ so
 909 that

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

919 We can then conclude that the conditions (A.7) and (A.13) are sufficient for
 920 1) the slower learners always prefers $(n = 0, e = e_H)$ over $(n = 0, e = 0)$, and 2)
 921 $\bar{z}_{fast} > \underline{z}_{fast}$, i.e., there exists state space where $(n = 1, e = e_L)$ is optimal.

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

923 For the fast learners, their cutoffs rank as follows

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

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

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

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

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

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

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

926 B Proof of Proposition

927 B.1 Proof of Proposition 2

928 The derivative of saving with respect to t is

$$\frac{\partial a^*}{\partial t}(x, a; t) = -\frac{x\mu}{1+\beta} + \frac{x^2\Sigma}{\beta} \frac{t[2(x+a) + tx\mu]}{[(x+a) + tx\mu]^2}. \quad (\text{B.1})$$

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

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

930 Define

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

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

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

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

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

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

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

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

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

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

938 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

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

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

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

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

942 B.2 Proof of Proposition 3

943 Denote

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

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

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

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

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

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

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

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

948

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

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

950 If

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

951 Then $\Delta_H(x, a; t) < x \left[-\frac{\beta}{1+\beta} + \frac{\Sigma}{\beta} G_\infty(t) \right] < 0$ for any x .

952 Furthermore, with some tedious algebra, we can show that for any x

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

953 Hence, the inequality (B.4) also implies that

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

954 B.3 Proof of Proposition 4

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

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

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

959 *B.4 Proof of Proposition 5*

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

960 differentiating with respect to t gives

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

961 Since

$$\frac{\partial^2 a'^*(x, a; t)}{\partial t^2} = \frac{\partial}{\partial t} \left(-\frac{x\mu}{1+\beta} + \frac{x^2\Sigma}{\beta} \frac{t[2(x+a) + tx\mu]}{[(x+a) + tx\mu]^2} \right) = \frac{2x^2\Sigma(a+x)^2}{\beta(a+x+tx\mu)^3} > 0. \quad (\text{B.6})$$

962 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 .

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

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

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

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

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

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

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

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

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

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

970 Since f is increasing,

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

971 which implies

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

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

973 Now for any $t' > t$,

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

974 and therefore

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

975 We then have that:

$$1 < t < t', \Delta_{\text{on-job}}(x, a; t) > 0 \implies \Delta_{\text{on-job}}(x, a; t') > \Delta_{\text{on-job}}(x, a; t) \quad (\text{B.7})$$

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

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

979 For $t < 1$,

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

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

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

981 Since f is increasing

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

982 which implies

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

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

984 Consider

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

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

986 If there exists some $t_s \in [t, t']$ such that $f(t_s) = 0$, so $f(u) < 0$ for $u < t_s$ and
987 $f(u) > 0$ for $u > t_s$. Then $f(u) > 0$ for $u \in [t', 1]$. Hence,

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

988 This implies that

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

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

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

990 We then have that

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

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

993 C Computational Procedure for the Quantitative Model

994 C.1 Steady-state Equilibrium

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

- 999 1. We choose the number of grid for the risk-free asset, a , human capital, h , and
1000 the idiosyncratic labor productivity, x . We set $N_a = 151$, $N_h = 151$, and
1001 $N_x = 9$ where N denotes the number of grid for each variable. To better
1002 incorporate the saving decisions of households near the borrowing constraint,
1003 we assign more points to the lower range of the asset and human capital.
- 1004 2. Productivity x is equally distributed on the range $[-3\sigma_x/\sqrt{1-\rho_x^2}]$. As shown
1005 in the paper, we construct the transition probability matrix $\pi(x'|x)$ of the
1006 idiosyncratic labor productivity.
- 1007 3. Given the values of parameters, we find the value functions for each state
1008 (a, h, x) . We also obtain the decision rules: savings $a'(a, h, x)$, and $h'(a, h, x)$.
1009 The computation steps are as follow:
- 1010 4. After obtaining the value functions and the decision rules, we compute the
1011 time-invariant distribution $\mu(a, h, x)$.
- 1012 5. If the variables of interest are close to the targeted values, we have found the
1013 steady-state. If not, we choose the new parameters and redo the above steps.

1014 C.2 Transition Dynamics

1015 We incorporate the transition path from the status quo to the new steady state. We
1016 describe the steps below.

- 1017 1. We obtain the initial steady state and the new steady state.
- 1018 2. We assume that the economy arrives at the new steady state at time T . We
1019 set the T to 100. The unit of time is a year.
- 1020 3. We initialize the capital-labor ratio $\{K_t/L_t\}_{t=2}^{T-1}$ and obtain the associated
1021 factor prices $\{r_t, w_t\}_{t=2}^{T-1}$.
- 1022 4. As we know the value functions at time T , we can obtain the value functions
1023 and the decision rules in the transition path from $t = T - 1$ to 1.
- 1024 5. We compute the measures $\{\mu_t\}_{t=2}^T$ with the measures at the initial steady state
1025 and the decision rules in the transition path.
- 1026 6. We obtain the aggregate variables in the transition path with the decision rules
1027 and the distribution measures.
- 1028 7. We compare the assumed paths of capital and the effective labor with the
1029 updated ones. If the absolute difference between them in each period is close
1030 enough, we obtain the converged transition path. Otherwise, we assume new
1031 capital-labor ratio and go back to 3.

1032 D Investigating the GE channel of AI's impact

1033 **Redistribution versus general equilibrium effects:** The effects of human cap-
1034 ital adjustments on AI's aggregate impacts operate through two primary channels:
1035 the *redistribution channel*, which reallocates households across skill sectors, and the
1036 *general equilibrium (GE) channel*, which operates through changes in wages and
1037 capital returns. We now assess the relative importance of these channels in shaping
1038 economic outcomes.

1039 Figure ?? compares the transition dynamics between scenarios with and without
1040 human capital adjustments, while holding wages and capital returns fixed at their
1041 initial steady-state levels to eliminate GE effects. We refer to the former as the
1042 "PE Model" and the latter as the "No-HC PE Model." The difference between the
1043 solid blue line and the dashed red line isolates the effect of redistribution channel.
1044 Comparing this difference to the gap between the benchmark model and the No
1045 HC model in Figure 6 enables us to evaluate the importance of the redistribution
1046 channel relative to the GE channel. Two key observations emerge.

1047 First, the *redistribution channel* alone accounts for all the *qualitative effects* of
1048 human capital adjustments on AI's aggregate impacts. Redistribution of human

Figure 8: Caption

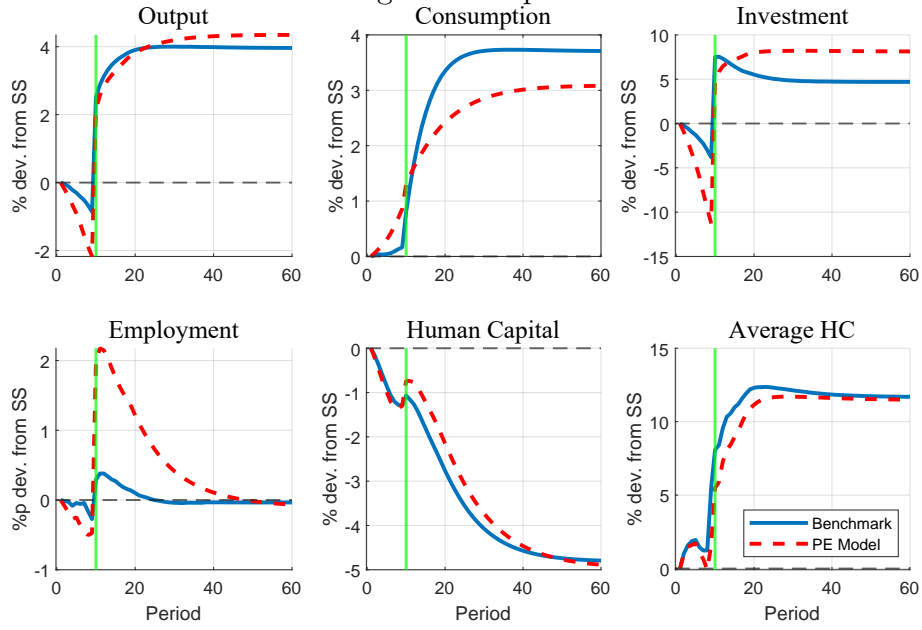
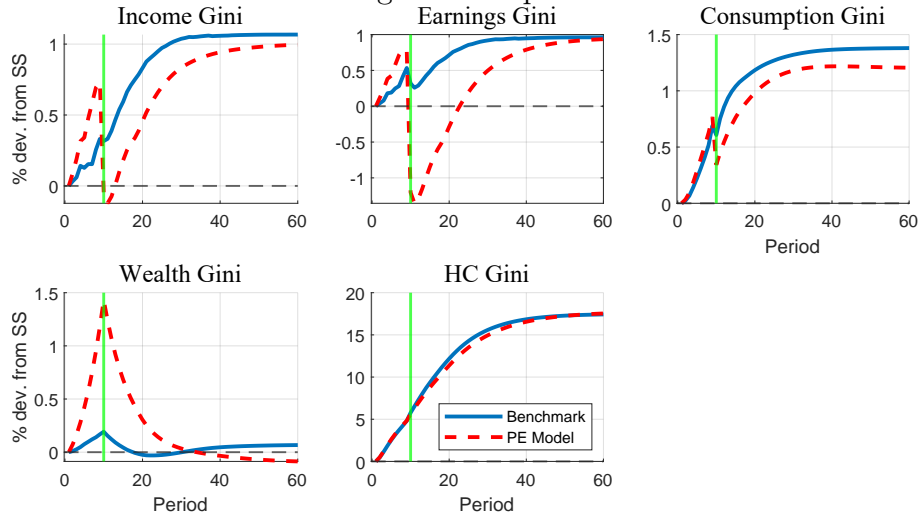


Figure 9: Caption



capital increases consumption, even before AI implementation, as more households shift to the high sector. It also reduces investment by mitigating precautionary savings and lowers employment as middle-sector workers leave the labor market to invest in human capital. In the long run, redistribution amplifies AI's positive impact on output by reallocating more workers to sectors that benefit most from AI advancements.

Second, the *GE channel* primarily affects the *quantitative magnitude* of human capital adjustments' impact on AI's aggregate outcomes. When the GE channel is included, the differences in output, consumption, and employment between models with and without human capital adjustments are smaller compared to when the GE channel is excluded. In contrast, and somewhat unexpectedly, the difference in investment is larger when the GE channel is included. This indicates that allowing capital returns to adjust amplifies the impact of human capital accumulation on how household savings respond to AI.

When the *GE channel* is active (Figure ??), AI reduces the wealth Gini, but the *redistribution channel* moderates this effect. However, when the *GE channel* is disabled (Figure ??), AI increases wealth inequality in the long run without the *redistribution channel* from human capital adjustment. In contrast, with the *redistribution channel* active, AI reduces wealth inequality.

These observations lead to two key conclusions:

First, the *redistribution channel* alone introduces a qualitative shift in AI's long-run impact on the wealth Gini (as shown in Figure ??).

Second, the *GE channel*, when combined with human capital adjustment, qualitatively alters the effect of anticipating AI on the wealth Gini (as shown by comparing the blue lines in Figures ?? and ??).

Policy implications: The impact of human capital adjustments on AI's distributional outcomes, along with the roles of the *redistribution channel* and *GE channel*, provides valuable insights for policy discussions on how to address the challenges posed by AI shocks.

In particular, government interventions aimed at stabilizing wages in response to AI-induced economic shocks may unintentionally worsen wealth inequality. Our analysis indicates that if wages are prevented from adjusting to reflect productivity differences, this distorts households' incentives to adjust their human capital and precautionary savings—both of which play a critical role in mitigating wealth inequality.