

AI and Human Capital Accumulation: Aggregate and Distributional Implications*

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Abstract

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

Keywords: AI, Job Polarization, Human Capital, Inequality

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¹ 1 Introduction

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

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

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

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

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

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

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

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

49 *1.2 Overview of our model and results*

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

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

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

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

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

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

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

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

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

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

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

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

114 1.3 Related Literature

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

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

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

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

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

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

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

164 2 Model Environment

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

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

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

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

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

175 2.1 Production Technology

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

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

178 K represents the total physical capital accumulated by households, while L denotes
179 the total effective labor supplied by households, aggregated across three sectors: low,

180 middle, and high. The marginal products of capital and effective labor determine
 181 the economy-wide wage rate, w , and interest rate, r .

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

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

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

$$L = \int n_i z_i x(h_i) di, \quad (5)$$

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

194 2.2 Household's Problem

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

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

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

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

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

$$c_t \geq 0 \text{ and } a_{t+1} \geq 0 \quad (8)$$

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

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

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

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

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

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

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

212 3 Household Decisions in a Two-Period Model

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

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

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

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

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

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

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

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

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

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

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

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

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

234 *3.1 Period-1 Labor Supply and Human Capital Investment*

235 **3.1.1 Consumption and saving without uncertainty**

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

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

239 The log utility in consumption implies the optimality condition:

$$c' = \beta(1+r')c. \quad (14)$$

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

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

242 **3.1.2 Labor supply and human capital investment**

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

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

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

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

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

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

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

252 These cutoffs divide households into three groups based on their ability to be em-
253 ployed in the middle sector in the next period. Conditional on y and learner type,
254 the optimal choices of labor supply and human capital investment are characterized
255 by cutoffs in \tilde{z} . The cutoff formulae below are stated in terms of z under the nor-
256 malization $x(h) = 1$. For households in other sectors, the corresponding cutoffs in z
257 are obtained by dividing by $x(h)$. To simplify notation, we define the effective labor
258 productivity $\tilde{z} := zx(h)$.

259 **Non-learners** are households with $h < \underline{h}_M(y)$. They cannot achieve $h' > h_M$
260 with either e_L or e_H level of human capital investment today. As a result, they will
261 choose not to invest in human capital, $e = 0$, and their future sectoral productivity
262 will be $x(h') = 1 - \lambda$.

263 These non-learners work $n = 1$ if and only if $z \geq \bar{z}_{non}^L(a)$:

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

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

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

$$\bar{z}_{slow}^L(a) = \frac{(\exp(\frac{\chi_n - \chi_e e_H}{1+\beta}) - 1)[(1+r)a + \frac{w'z'}{1+r'}] + \lambda \frac{w'z'}{1+r'}}{w} \quad (19)$$

271 **Fast learners** are households with $h > \bar{h}_M(y)$. They can achieve $h' > h_M$ in
272 the next period if they invest $e = e_L$ today. In this case, there is no need to exert
273 high effort e_H in human capital investment. The fast learners choose among three

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

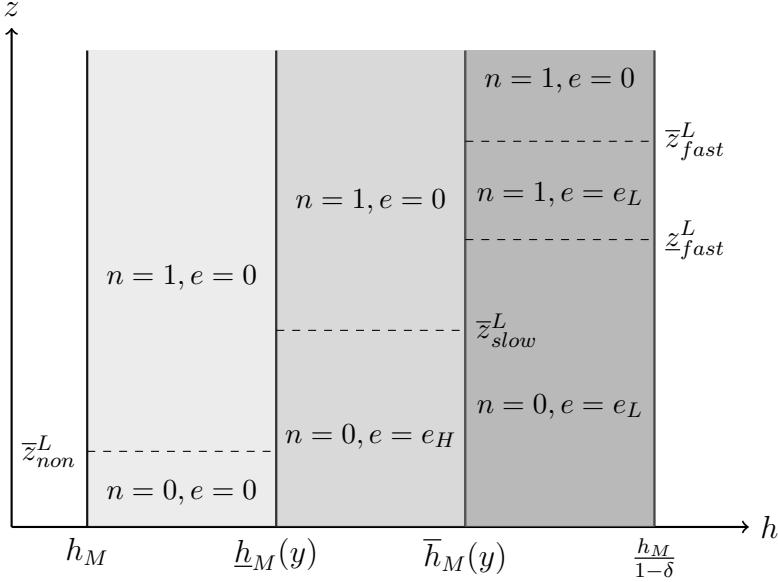


Figure 1: Decision Rule Diagram for $h_M \leq h < h_M(1 - \delta)^{-1}$

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

²⁷⁴ options: $(n = 1, e = 0)$, $(n = 1, e = e_L)$, and $(n = 0, e = e_L)$.⁷

²⁷⁵ The decision rule for fast learners are as follows:

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

²⁷⁶ where

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

²⁷⁷

$$\underline{z}_{fast}^L(a) = \frac{\left(\exp\left(\frac{\chi_n}{1+\beta}\right) - 1 \right) [(1+r)a + \frac{w' z'}{1+r'}]}{w} \quad (22)$$

²⁷⁸ We set up our model so that $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.⁸

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

⁸Appendix 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 $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.

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

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

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

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

290 If $h_M \frac{1}{1-\delta} \leq h < h_H$, the four cutoffs that partition the decision regions for households
291 are denoted as $\bar{z}_{non}^M(a)$, $\bar{z}_{slow}^M(a)$, $\underline{z}_{fast}^M(a)$, and $\bar{z}_{fast}^M(a)$ (see Appendix A.1 for the
292 explicit formulae).⁹ If $h_H \leq h < h_H \frac{1}{1-\delta}$, the analogous cutoffs are given by $\bar{z}_{non}^M \frac{1}{1+\lambda}$,
293 $\bar{z}_{slow}^M \frac{1}{1+\lambda}$, $\underline{z}_{fast}^M \frac{1}{1+\lambda}$, and $\bar{z}_{fast}^M \frac{1}{1+\lambda}$.

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

297 3.2 The Effects of Uninsured Idiosyncratic Risk

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

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

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

310 From the perspective of human capital investment, the uncertain z' is associated with risk in the return to human capital. Conditional on working, households'
311 income increases with z' : $c' = (1 + r')a' + w'x(h')z'$. $\ln(c')$ is increasing and concave

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

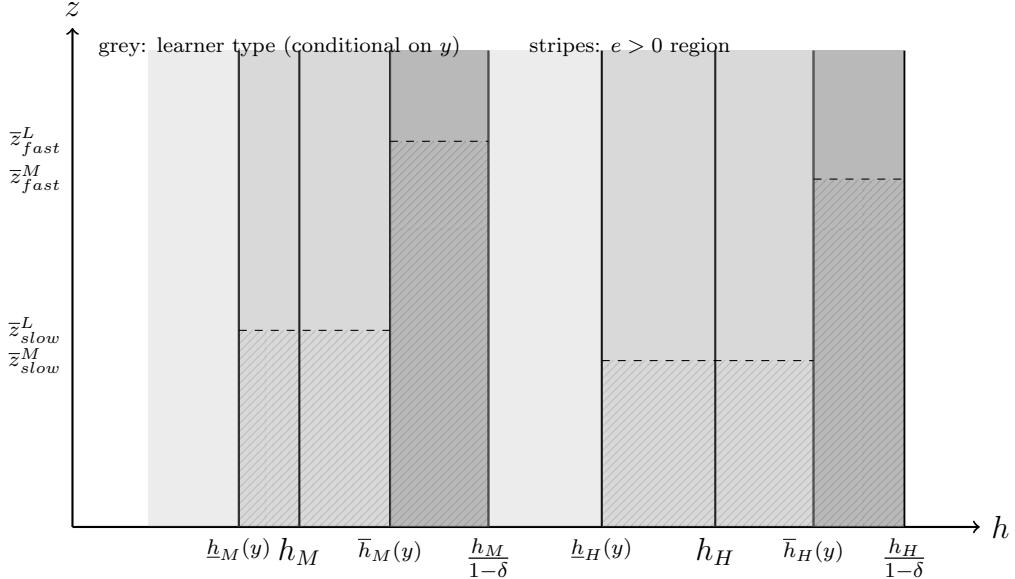


Figure 2: State Space for Human Capital Investment

With a separate learning-ability shock y , the figure illustrates how learner type (grey shading) and optimal investment ($e > 0$, striped areas) vary with the labor productivity shock z and human capital h . The cutoffs in h are conditional on y ; the cutoffs in z are scaled by current-sector productivity $x(h)$.

in z' , and a higher $x(h')$ increases the concavity.¹⁰ 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.*

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

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

The second derivative is

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

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

³²⁷ 3.3 Period-1 Saving and Human Capital Investment

³²⁸ In this section, we study the impact of endogenous human capital investment on
³²⁹ households' saving decisions. Specifically, we compare optimal saving behavior in
³³⁰ two scenarios: one in which households can choose to invest in human capital, and
³³¹ an alternative scenario in which human capital is exogenously fixed. To facilitate the
³³² comparison, we assume in this section that there is no human capital depreciation.¹¹

³³³ When the optimal choice of human capital investment is zero, optimal saving is
³³⁴ identical in both scenarios. When the optimal human capital investment is either e_L
³³⁵ or e_H , we compare the household's optimal saving to the case where human capital
³³⁶ investment is exogenously fixed at zero, i.e., $(n = 1, e = 0)$.¹²

³³⁷ To make the human capital relevant, we assume that $n' = 1$ in period 2. The
³³⁸ additive separability of work and human capital investment effort from consumption
³³⁹ allows us to consider the optimal saving conditional on a given choice of labor supply
³⁴⁰ and human capital investment.

³⁴¹ In particular, the household maximizes expected lifetime utility:

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

³⁴² subject to the budget constraints

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

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

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

³⁴³ 3.3.1 Effect of on-job-training on saving

³⁴⁴ We now compare the optimal saving between $(n = 1, e = e_L)$ and $(n = 1, e = 0)$,
³⁴⁵ where e_L allows households to move to a higher sector in period 2 with higher
³⁴⁶ sectoral productivity $x(h')$.

³⁴⁷ To simplify the notation while maintaining the key economic forces, we normalize
³⁴⁸ $(1 + r) = (1 + r') = 1$, $w = w' = 1$, the period-1 productivity shock $z = 1$, the
³⁴⁹ period-1 learning-ability shock $y = 1$, and the period-2 productivity shock z' to

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

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

³⁵⁰ $\ln z' \sim \mathcal{N}(0, \sigma_z^2)$. The budget constraints become:

$$c + a' = a + x, \quad c' = a' + txz' \quad (28)$$

³⁵¹ where x is the household's period-1 labor income that reflects both productivity and
³⁵² skill. $t \geq 1$ represents the effect of human capital investment on period-2 income:
³⁵³ $t > 1$ if $e = e_L$; $t = 1$ if $e = 0$.

³⁵⁴ The optimal saving is determined by the FOC:

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

³⁵⁵ Denoting the mean and variance of z' as μ and Σ , respectively:

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

³⁵⁶ The second-order approximate solution to the FOC is:

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

³⁵⁷ The first term is the *certainty-equivalent* saving, which reflects the consumption
³⁵⁸ smoothing motive, increasing in the period-1 resources $a + x$ and decreasing in the
³⁵⁹ period-2 expected labor income $tx\mu$. The second term is the *precautionary* saving,
³⁶⁰ which is increasing in the variance of period-2 labor income $t^2 x^2 \Sigma$ and decreasing in
³⁶¹ the expected total resources $a + x + tx\mu$.

³⁶² The effect of on-job-training on saving can be decomposed into two components:

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

³⁶³ The first term being negative captures the *crowd-out* effect on saving via consumption-
³⁶⁴ smoothing motive as on-job-training increases the expected period-2 labor income
³⁶⁵ $tx\mu$. The second positive term captures the *crowd-in* effect via precautionary saving
³⁶⁶ motive as on-job-training exposes households to larger future income risk.

³⁶⁷ To capture the overall impact of on-job-training on saving, we define:

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

³⁶⁸ where $a'^*(x, a; t)$ is the optimal saving when households undertake on-job-training,
³⁶⁹ and $a'^*(x, a; 1)$ is the optimal saving when human capital is kept exogenously fixed.

³⁷⁰ Whether on-job-training increases or decreases saving ultimately depends on
³⁷¹ the balance between the crowd-out effect (via higher expected future income) and

372 the precautionary crowd-in effect (via heightened future income risk). The next
 373 proposition demonstrates that these effects can dominate differently depending on
 374 period-1 income x , so that the overall impact of on-job-training on saving can differ
 375 between low- and high-income households.

376 **Proposition 2.** *If the idiosyncratic risk is large enough, i.e., $\frac{\Sigma}{\mu} > \sigma^*(t)$, on-job-
 377 training crowds out saving for low-income households and crowds in saving for high-
 378 income households: for $x < x^*(a, t)$, $e = e_L$ lowers saving $\Delta_{on\text{-}job}(x, a; t) < 0$; for
 379 $x > x^*(a, t)$, $e = e_L$ raises saving $\Delta_{on\text{-}job}(x, a; t) > 0$.*

380 *Proof.* See Appendix B. □

381 3.3.2 Effect of full-time training on saving

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

$$e = e_H : c + a' = a, \quad c' = a' + txz' \quad (34)$$

$$e = 0 : c + a' = a + x, \quad c' = a' + xz' \quad (35)$$

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

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

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

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

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

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

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

390 Here, $\Delta_H(x, a; t)$ captures the additional impact of full-time training on saving, over
 391 and above that of on-job-training. The first term reflects a further reduction in
 392 saving due to the need to forgo period-1 labor income. The second term shows

393 an increase in precautionary saving, as reduced current resources limit households'
 394 ability to self-insure against idiosyncratic risk in period 2.

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

396 **Lemma 1.** *If $\frac{\Sigma}{\mu} < \hat{\sigma}(t)$, $\Delta_H(x, a; t) < 0$ and decreases in x . If $\frac{\Sigma}{\mu} > \bar{\sigma}(t)$, $\Delta_H(x, a; t) >$
 397 0 if and only if $x > \hat{x}(a, t)$; moreover, for $x > \hat{x}(a, t)$, $\Delta_H(x, a; t)$ increases in x .*

398 *Proof.* See Appendix B. □

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

402 **Proposition 3.** *If the idiosyncratic risk is large enough, i.e., $\frac{\Sigma}{\mu} > \max\{\sigma^*(t), \hat{\sigma}(t)\}$,
 403 full-time training *crowds out* saving for low-income households and *crowds in* sav-
 404 ing for high-income households: for $x < \min\{x^*(a, t), \hat{x}(a, t)\}$, $e = e_H$ lowers
 405 saving $\Delta_{full-time}(x, a; t) < 0$; for $x > \max\{x^*(a, t), \hat{x}(a, t)\}$, $e = e_H$ raises saving
 406 $\Delta_{full-time}(x, a; t) > 0$.*

407 3.4 The Effects of an Anticipated Period-2 AI Shock

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

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

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

414 3.4.1 Effects on human capital investment

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

422 **Proposition 4.** *An anticipated AI shock decreases human capital investment among
 423 households with $h < h_M/(1 - \delta)$, but increases it among those with $h > h_M/(1 - \delta)$.
 424 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 .*

425 *Proof.* See Appendix B. □

426 3.4.2 Effects on labor supply

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

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

437 3.4.3 Effects on saving

438 The AI shock increases sectoral labor productivity for the low and high sectors in
439 period 2, while leaving the middle sector's labor productivity unchanged. Its effect
440 on saving can be analyzed as if we are varying the parameter t in the functions
441 $\Delta_{\text{on-job}}(x, a; t)$, defined in (33), and $\Delta_H(x, a; t)$, defined in (39).

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

- 443 • 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 $t' > t > 1$.
- 444 • 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 $1 > t' > t$.

445 *Proof.* See Appendix B. □

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

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

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

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

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

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

471 For the middle-sector households who upskill via full-time training, there is an
472 *additional positive effect* of the AI shock on their saving, because a higher x' increases
473 $\Delta_H(x, a; t)$ (Proposition 5).

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

478 For middle-sector households who downskill to the low sector, their saving differs
479 from the fixed human capital scenario by $\Delta_{\text{on-job}}(x, a; t)$ with $t < 1$. The AI shock
480 mitigates their future productivity loss by reducing it from λ to $(1 - \gamma)\lambda$, effectively
481 increasing t to a new value $t' < 1$. According to Proposition 5, if the pre-shock effect
482 $\Delta_{\text{on-job}}(x, a; t)$ is positive, the AI shock will *reduce* saving. If this effect is negative,
483 however, the overall impact of the AI shock on saving is ambiguous.

484 3.5 Limitations of the two-period model

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

492 **General equilibrium (GE) effects** When households adjust their investment in
493 human capital, labor supply, and savings in response to AI, these changes aggregate

494 up to affect the total supply of effective labor and capital in the economy. As these
495 aggregates shift, they exert downward or upward pressure on the wage rate and
496 the interest rate, feeding back into each household's optimization problem. Thus,
497 general equilibrium effects capture the intricate loop by which individual decisions
498 shape, and are shaped by, the macroeconomic environment.

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

505 4 A Quantitative Model

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

509 4.1 Calibration

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

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

518 We calibrate parameters regarding labor productivity process as follows. We
519 assume that z follows the AR(1) process in logs: $\log z' = \rho_z \log z + \epsilon_z$, where $\epsilon_z \sim$
520 $N(0, \sigma_z^2)$. The shock process is discretized using the **tauchen1986finite** method,
521 resulting in a transition probability matrix with 11 grids. We set the persistence
522 parameter to $\rho_z = 0.948$ and the standard deviation to $\sigma_z = 0.269$, following the
523 estimates reported in Chang and Kim (2006).

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

Table I: Parameters for the Calibration

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

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

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

539 4.2 Key Moments: Data vs. Model

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

Table II: Key Moments

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

552 outcomes and the corresponding distributional aspects of earnings. Although the
 553 model does not explicitly target the wealth Gini coefficient, it achieves a close match
 554 to the data: the empirical wealth Gini is 0.78, while the model produces a value of
 555 0.76. This highlights the model's ability to capture substantial wealth inequality in
 556 the economy.

557 4.3 Steady-state Distribution

558 Table III presents the steady-state distribution of population, employment, and
 559 assets across sectors. The population shares are calibrated to 20%, 40%, and
 560 40% by adjusting the human capital thresholds that define sectors. The shares
 561 of employment and assets are endogenously determined by households' labor supply
 562 and savings decisions. Notably, the high sector accounts for 46% of total employ-
 563 ment—exceeding its population share—indicating that a disproportionate number
 564 of households choose to work in that sector. Asset holdings are even more skewed:
 565 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

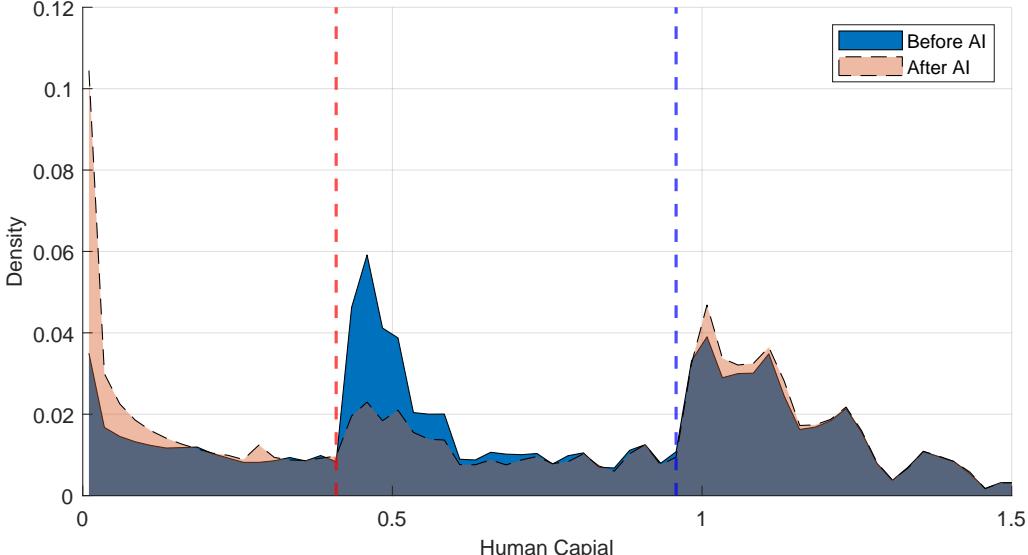
Note: Human capital cutoffs, h_H and h_M , determine the population share across sectors. Employment share and assets share are implied by households labor supply decisions and saving decisions.

566 5 AI's Impact on Human Capital Adjustments

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

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

Figure 3: Steady-state Human Capital Distribution



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

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

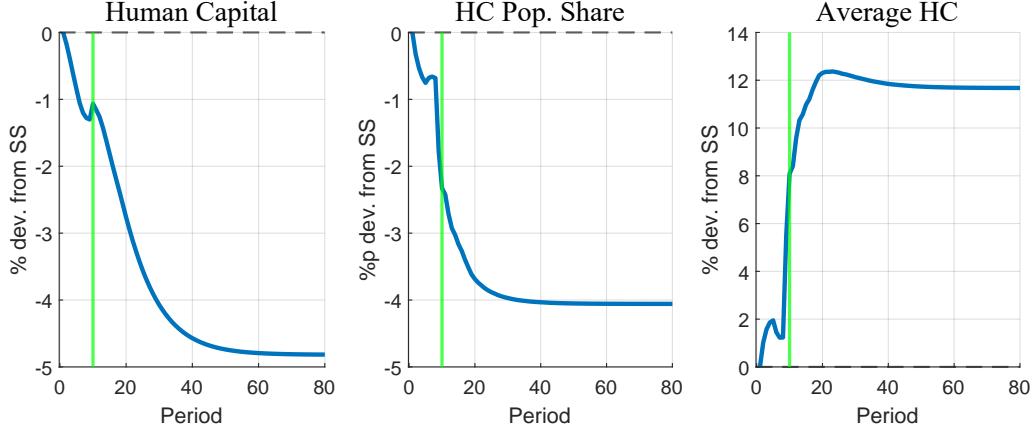
578 5.1 Human Capital Adjustments

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

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

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

Figure 4: Transition Path for Human Capital Investment



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

⁵⁹⁷ lower end of the low sector and the lower end of the high sector.

⁵⁹⁸ **Transition path** Figure 4 reports the transition dynamics of aggregate human
⁵⁹⁹ capital from the initial to the new steady state. The figure also displays its extensive
⁶⁰⁰ margin (the share of households making positive human capital investments) and
⁶⁰¹ intensive margin (average human capital per household among those who invest).

⁶⁰² As households reallocate from the middle sector to the low and high sectors, the
⁶⁰³ net effect is a gradual decline in aggregate human capital along the transition path.
⁶⁰⁴ This mirrors the steady-state change observed in Figure 3, where the increased mass
⁶⁰⁵ at the lower end of the low sector outweighs the increase in the high sector.

⁶⁰⁶ Additionally, human capital accumulation becomes increasingly concentrated
⁶⁰⁷ among a smaller share of the population. The proportion of households making
⁶⁰⁸ positive human capital investments steadily declines, ultimately stabilizing at a level
⁶⁰⁹ 4% lower than in the initial steady state. Meanwhile, the average human capital
⁶¹⁰ among those who invest rises, reaching a level 12% higher than the initial steady
⁶¹¹ state in the long run.¹³

⁶¹² 5.2 Job Polarization

⁶¹³ An important implication of human capital adjustments to the AI shock is job
⁶¹⁴ polarization. Figure 5 illustrate the transition paths of population shares and em-
⁶¹⁵ ployment rates in each sector. Notably, the middle sector experiences a significant
⁶¹⁶ decline, with its population share decreasing by approximately 13%. Additionally,
⁶¹⁷ employment within this sector plummets to a level 16% lower than the initial steady
⁶¹⁸ state. In contrast, both the low and high sectors see increases in their population

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

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

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

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

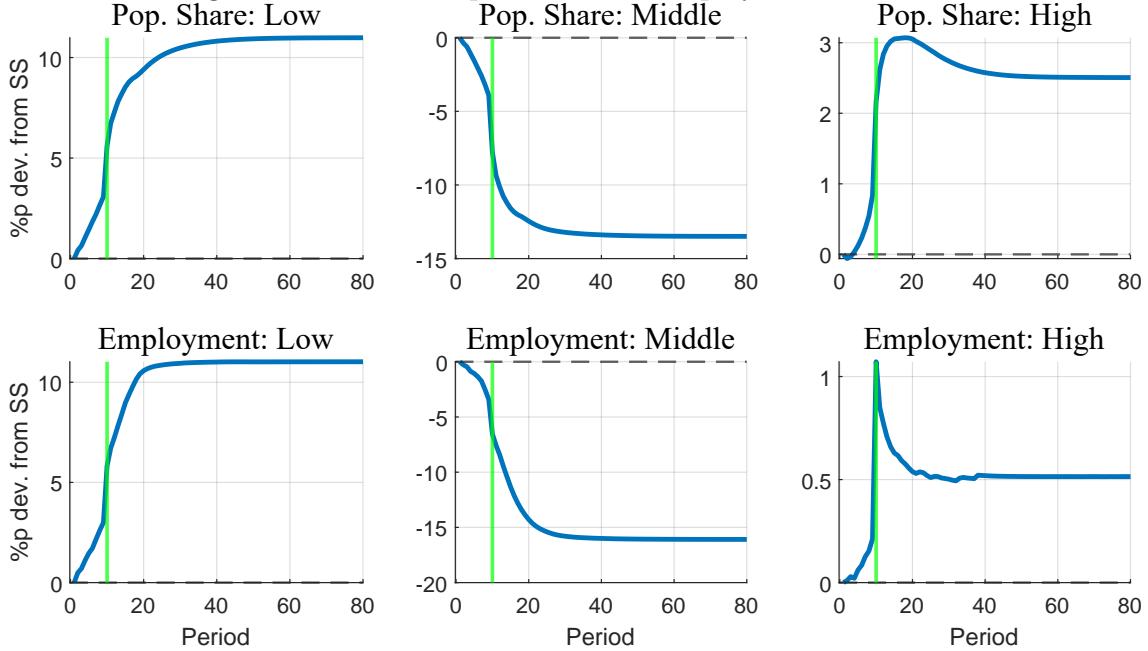
This disparity arises from two key factors. First, AI enhances the productivity of low-sector workers by 7.5% and high-sector workers by 5%. However, this productivity differential alone does not fully account for the significant asymmetry. The second factor is the variation in labor supply elasticity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

6 The Aggregate and Distributional Effects of AI

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

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

Figure 5: Sectoral Population and Employment Transition



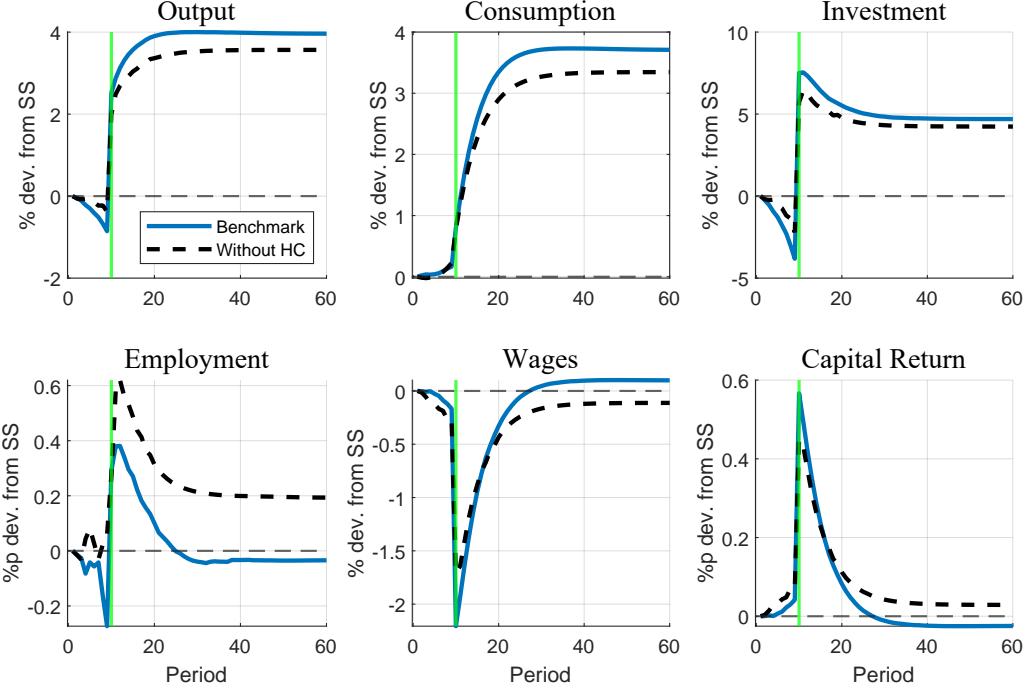
Note: The transition paths within each sector. The x-axis represents years, and the y-axis shows the percentage (or percentage point) deviation from the initial steady state. AI introduction is assumed to occur in period 10. “Pop. Share” denotes the population share within each sector. “Employment” is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

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

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

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

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



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

674 6.1 Aggregate Implications

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

680 6.1.1 AI's direct impacts

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

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

693 Following the AI shock, sectoral productivity in the low and high sectors rises,

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

6.1.2 AI's indirect impacts via endogenous human capital adjustments

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

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

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

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

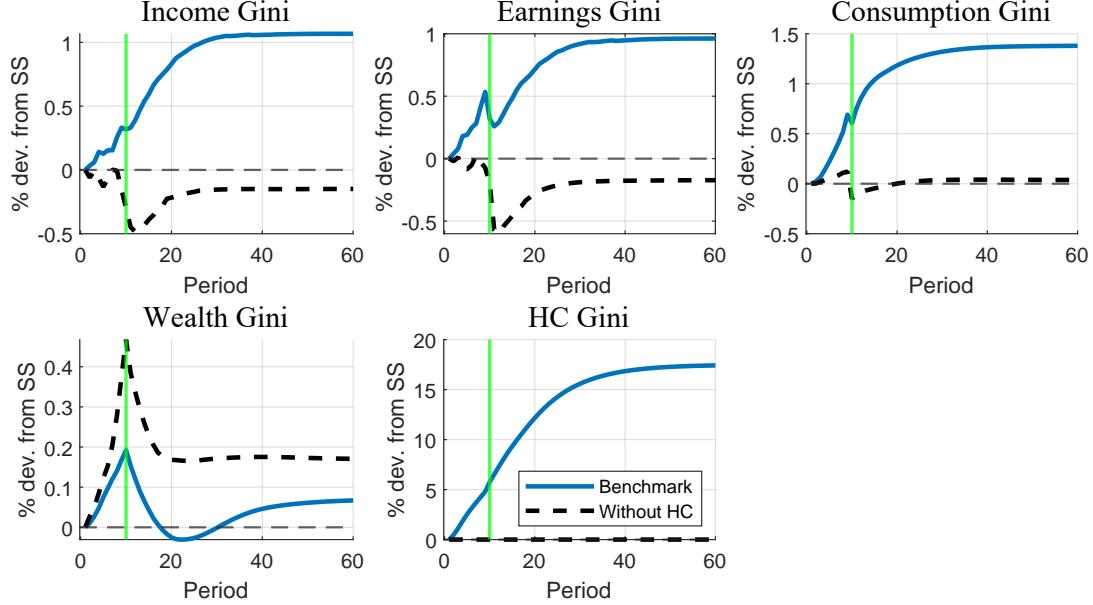
6.2 Distributional Implications

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

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

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

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



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

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

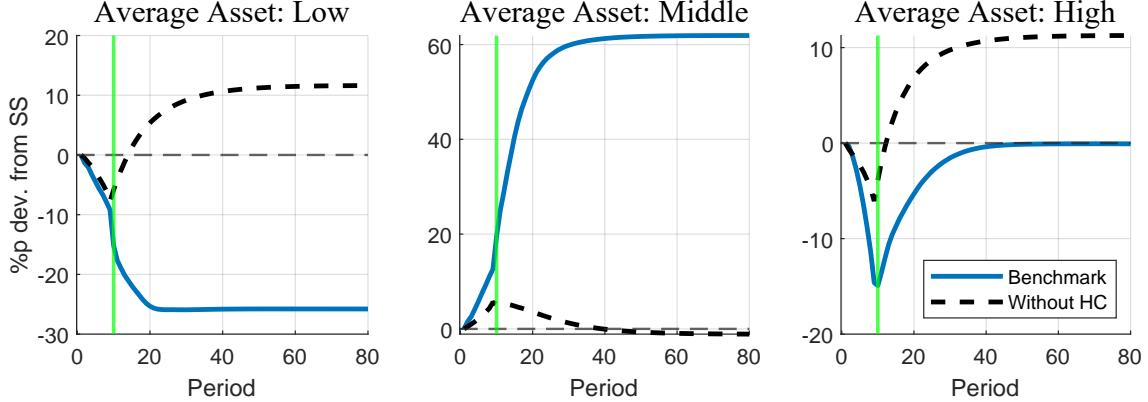
735 6.2.1 Income, earnings, and consumption inequalities

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

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

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

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



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

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

6.2.2 Wealth inequality

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

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

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

775 households across sectors.

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

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

801 7 Conclusion

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

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

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

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

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912 **A Household Decision Rule Cutoffs**

913 *A.1 Additional cutoffs formulae for households*

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

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

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

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

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

914 *A.2 Parameter restrictions for cutoffs ranking*

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

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

917 or equivalently:

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

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

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

924 that

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

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

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

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

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

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

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

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

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

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

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

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

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

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

931 Therefore, the inequality above implies that the conditions (A.6) and (A.7) are
932 sufficient for the conditions (A.11) and (A.12). Furthermore, $\underline{\lambda}_3 \geq \underline{\lambda}_1$ so that the
933 condition (A.7) is sufficient for the condition (A.6).

934 We can then conclude that the conditions (A.7) and (A.13) are sufficient for
935 1) the slower learners always prefers $(n = 0, e = e_H)$ over $(n = 0, e = 0)$, and 2)
936 $\bar{z}_{fast} > \underline{z}_{fast}$, i.e., there exists state space where $(n = 1, e = e_L)$ is optimal.

⁹³⁷ A.3 Other cutoffs ranking for the two-period Model

⁹³⁸ For the fast learners, their cutoffs rank as follows

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

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

⁹³⁹ For the slow learners, the rank of their cutoffs is

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

⁹⁴⁰ For the non-learners, the rank of their cutoffs is

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

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

⁹⁴¹ **B Proof of Proposition**

⁹⁴² *B.1 Proof of Proposition 2*

⁹⁴³ The derivative of saving with respect to t is

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

⁹⁴⁴ The total effect of on-job-training on saving is

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

⁹⁴⁵ Define

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

⁹⁴⁶ Then equation (B.2) can be written as

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

⁹⁴⁷ Differentiating $F(x, a; u)$ with respect to x gives

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

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

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

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

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

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

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

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

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

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

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

957 B.2 Proof of Lemma 1

958 Denote

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

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

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

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

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

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

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

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

963

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

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

965 If

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

⁹⁶⁶ Then $\Delta_H(x, a; t) < x[-\frac{\beta}{1+\beta} + \frac{\Sigma}{\beta}G_\infty(t)] < 0$ for any x . Furthermore, with some
⁹⁶⁷ tedious algebra, we can show that for any x

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

⁹⁶⁸ Hence, the inequality (B.6) also implies that

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

⁹⁶⁹ If $\frac{\Sigma}{\beta}G_\infty(t) > \frac{\beta}{1+\beta}$, i.e. $\frac{\Sigma}{\mu} > \hat{\sigma}(t) \equiv \frac{\beta^2}{1+\beta}(\frac{1}{t} + \mu)$, (B.6)

⁹⁷⁰ since $G(x, a; t)$ is strictly increasing in x , there exists a unique $\hat{x}(a, t)$ such that

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

⁹⁷¹ Moreover, $\Delta_H(x, a; t) > 0$ implies that

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

⁹⁷² B.3 Proof of Proposition 4

⁹⁷³ The relevant upper bounds of z for positive human capital investment are functions
⁹⁷⁴ of γ (to the first order approximation):

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

⁹⁷⁵ Therefore, an anticipated AI shock, $\gamma > 0$ makes those with $h < h_M \frac{1}{1-\delta}$ invest less
⁹⁷⁶ human capital and those with $h > h_M \frac{1}{1-\delta}$ invest more human capital.

⁹⁷⁷ B.4 Proof of Proposition 5

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

⁹⁷⁸ differentiating with respect to t gives

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

⁹⁷⁹ Since

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

⁹⁸⁰ 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 .

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

⁹⁸¹ Differentiating $G(x, a; t)$ with respect to t gives

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

⁹⁸² so $G(x, a; t)$ is strictly increasing in t , and so is $\Delta_H(x, a; t)$.

⁹⁸³ We now consider the comparison between $\Delta_{\text{on-job}}(x, a; t)$ and $\Delta_{\text{on-job}}(x, a; t')$ for $t' > t$. Given x and a , define

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

⁹⁸⁵ so $f'(t) > 0$, i.e. $f(t)$ is strictly increasing in t .

⁹⁸⁶ **Case 1:** $1 < t < t'$

⁹⁸⁷ Suppose $\Delta_{\text{on-job}}(x, a; t) > 0$. Then

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

⁹⁸⁸ Since f is increasing,

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

⁹⁸⁹ which implies

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

⁹⁹⁰ Because $t > 1$, the inequality $\Delta_{\text{on-job}}(x, a; t) > 0$ forces $f(t) > 0$.

⁹⁹¹ Now for any $t' > t$,

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

⁹⁹² and therefore

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

⁹⁹³ We then have that:

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

⁹⁹⁴ That is, once $\Delta_{\text{on-job}}(x, a; t)$ becomes positive for $t > 1$, it is strictly increasing in t
⁹⁹⁵ thereafter.

⁹⁹⁶ **Case 2:** $t < t' < 1$

⁹⁹⁷ For $t < 1$,

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

⁹⁹⁸ Suppose $\Delta_{\text{on-job}}(x, a; t) > 0$. Then

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

⁹⁹⁹ Since f is increasing

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

¹⁰⁰⁰ which implies

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

¹⁰⁰¹ Because $t < 1$, the inequality $\Delta_{\text{on-job}}(x, a; t) > 0$ forces $f(t) < 0$.

¹⁰⁰² Consider

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

¹⁰⁰³ If $f(u) < 0$ for all $u \in [t, t']$, then $\int_t^{t'} f(u) du < 0$.

¹⁰⁰⁴ If there exists some $t_s \in [t, t']$ such that $f(t_s) = 0$, so $f(u) < 0$ for $u < t_s$ and
¹⁰⁰⁵ $f(u) > 0$ for $u > t_s$. Then $f(u) > 0$ for $u \in [t', 1]$. Hence,

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

¹⁰⁰⁶ This implies that

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

¹⁰⁰⁷ Together with the inequality $\Delta_{\text{on-job}}(x, a; t) > 0$, we have that

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

1008 We then have that

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

1009 Thus, for $t < 1$, whenever $\Delta_{\text{on-job}}(x, a; t) > 0$, increasing t toward 0 makes $\Delta_{\text{on-job}}$
1010 strictly decrease.

1011 C Computational Procedure for the Quantitative Model

1012 C.1 Steady-state Equilibrium

1013 In the steady-state, the measure of households, $\mu(a, h, z)$, and the factor prices are
1014 time-invariant. We find a time-invariant distribution μ . We compute the house-
1015 holds' value functions and the decisions rules, and the time-invariant measure of the
1016 households. We take the following steps:

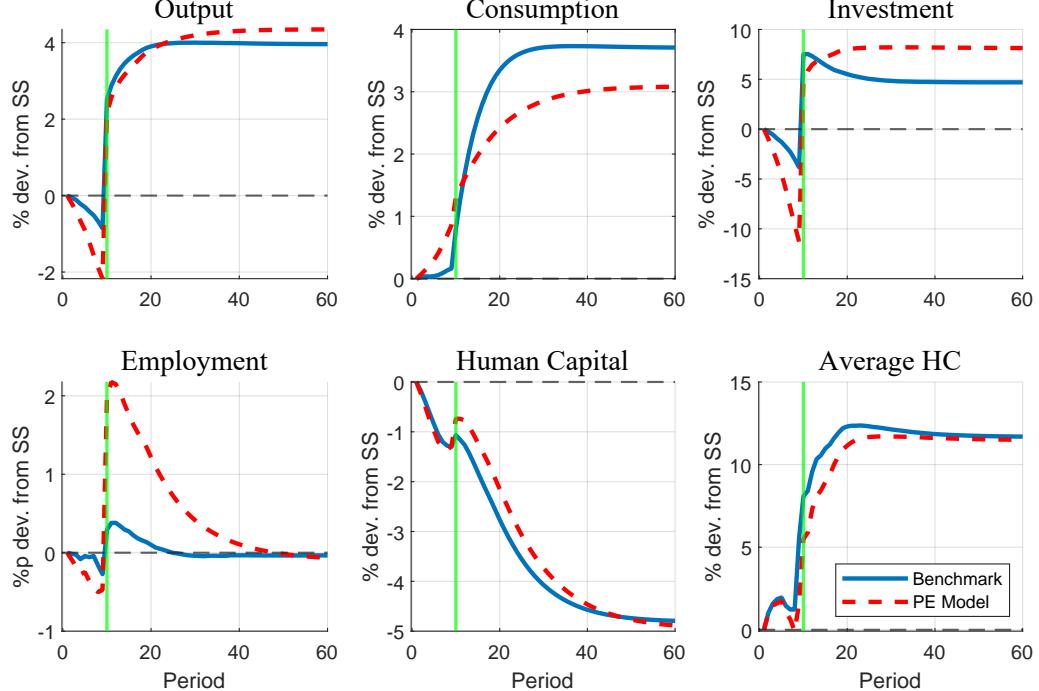
- 1017 1. We choose the number of grid for the risk-free asset, a , human capital, h , and
1018 the idiosyncratic labor productivity, z . We set $N_a = 151$, $N_h = 151$, and
1019 $N_z = 9$ where N denotes the number of grid for each variable. To better
1020 incorporate the saving decisions of households near the borrowing constraint,
1021 we assign more points to the lower range of the asset and human capital.
- 1022 2. Productivity z is equally distributed on the range $[-3\sigma_z/\sqrt{1 - \rho_z^2}]$. As shown
1023 in the paper, we construct the transition probability matrix $\pi(z'|z)$ of the
1024 idiosyncratic labor productivity.
- 1025 3. Given the values of parameters, we find the value functions for each state
1026 (a, h, z) . We also obtain the decision rules: savings $a'(a, h, z)$, and $h'(a, h, z)$.
1027 The computation steps are as follow:
- 1028 4. After obtaining the value functions and the decision rules, we compute the
1029 time-invariant distribution $\mu(a, h, z)$.
- 1030 5. If the variables of interest are close to the targeted values, we have found the
1031 steady-state. If not, we choose the new parameters and redo the above steps.

1032 C.2 Transition Dynamics

1033 We incorporate the transition path from the status quo to the new steady state. We
1034 describe the steps below.

- 1035 1. We obtain the initial steady state and the new steady state.
- 1036 2. We assume that the economy arrives at the new steady state at time T . We
1037 set the T to 100. The unit of time is a year.

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



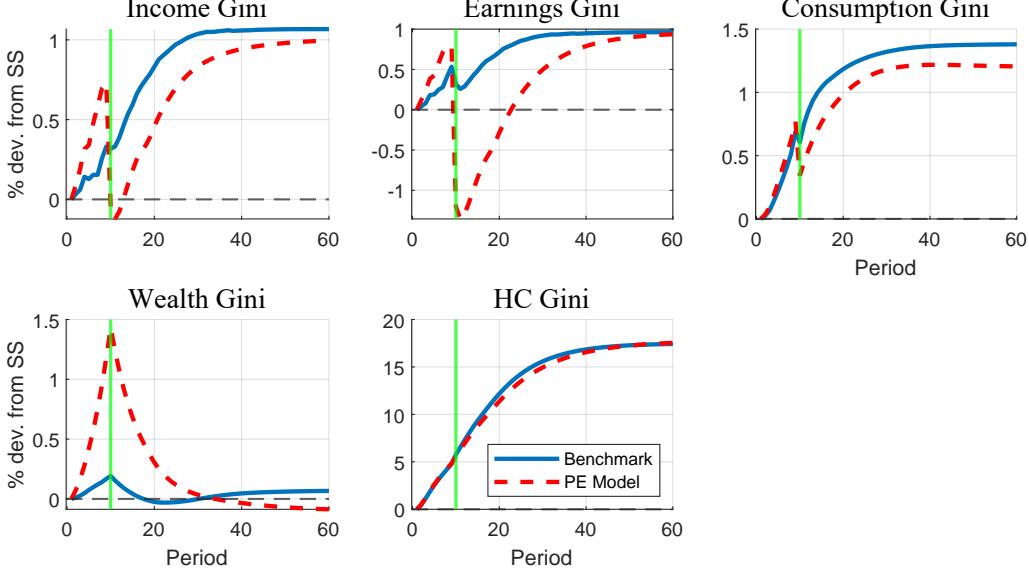
Note: The transition paths of aggregate variables: benchmark vs. PE models. The x-axis represents years, and the y-axis shows the percentage deviation from the initial steady state. AI introduction is assumed to occur in period 10. The PE model is an economy in which factor prices are held fixed at their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

- 1038 3. We initialize the capital-labor ratio $\{K_t/L_t\}_{t=2}^{T-1}$ and obtain the associated
1039 factor prices $\{r_t, w_t\}_{t=2}^{T-1}$.
- 1040 4. As we know the value functions at time T , we can obtain the value functions
1041 and the decision rules in the transition path from $t = T - 1$ to 1.
- 1042 5. We compute the measures $\{\mu_t\}_{t=2}^T$ with the measures at the initial steady state
1043 and the decision rules in the transition path.
- 1044 6. We obtain the aggregate variables in the transition path with the decision rules
1045 and the distribution measures.
- 1046 7. We compare the assumed paths of capital and the effective labor with the
1047 updated ones. If the absolute difference between them in each period is close
1048 enough, we obtain the converged transition path. Otherwise, we assume new
1049 capital-labor ratio and go back to 3.

1050 D Investigating the GE channel of AI's impact

1051 Figures 9 and 10 compare the transition dynamics in the benchmark general-equilibrium
1052 model with those in a partial-equilibrium (PE) version of the model, where individ-
1053 ual behavior responds to AI adoption but factor prices are held fixed at their initial
1054 steady-state values. The green vertical line marks the date of AI adoption.

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



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

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

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

¹⁰⁷⁹ Gini converges to a level similar to the benchmark, mainly because middle-sector
¹⁰⁸⁰ households gradually increase their savings, as discussed in the main text.