

# 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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## <sup>1</sup> 1 Introduction

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

### <sup>13</sup> 1.1 *Evidences for AI’s effects on skill premia*

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

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

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

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

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.<sup>2</sup>

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,

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

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.<sup>3</sup>

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<sup>3</sup>According 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  $\delta_h$  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.<sup>4</sup>

### 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

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

<sup>4</sup>The learning ability shock  $y_t$  is likely to be correlated with the labor productivity shock  $z_t$  in reality. In our quantitative analysis, we assume they are perfectly correlated to reduce the dimensionality of the state space. For readers interested in the two-period model under this perfect-correlation assumption, Appendix A.3 displays the corresponding decision rule diagram.

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  $e$ :<sup>5</sup>

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

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

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<sup>5</sup>This 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. **Non-learners** are households with  
254  $h < \underline{h}_M(y)$ . They cannot achieve  $h' > h_M$  with either  $e_L$  or  $e_H$  level of human  
255 capital investment today. **Slow learners** are households with  $h \in (\underline{h}_M(y), \bar{h}_M(y))$ .  
256 These households can reach  $h' > h_M$  in the next period only by investing  $e = e_H$   
257 today. **Fast learners** are households with  $h > \bar{h}_M(y)$ . They can achieve  $h' > h_M$   
258 in the next period if they invest  $e = e_L$  today.

259 Conditional on  $y$  and learner type, the optimal choices of labor supply and human  
260 capital investment are characterized by cutoffs in  $z$ . The cutoff formulae varies with  
261 households' current sectoral productivity, i.e, if  $h < h_M$  or not.

262 **Non-learners** will not invest in human capital,  $e = 0$ , and their future sectoral  
263 productivity will be  $x(h') = 1 - \lambda$ . Non-learners work  $n = 1$  if and only if:

$$z \geq \bar{z}_{non}^L(a, h) = \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1) \left[ (1+r)a + \frac{w'z'(1-\lambda)}{1+r'} \right]}{w(1 - \mathbb{1}_{h < h_M} \lambda)} \quad (18)$$

264 **Slow learners** choose between  $e = 0$  and  $e = e_H$ , since  $e = e_L$  incurs a cost  
265 without any future benefit. Slow learners must trade off between working and human  
266 capital investment: choosing  $e = e_H$  requires not working today ( $n = 0$ ), while  
267 opting to work means forgoing investment in human capital ( $n = 1, e = 0$ ).<sup>6</sup>

268 Slow learners prefer  $(n = 1, e = 0)$  to  $(n = 0, e = e_H)$  if and only if:

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

269 **Fast learners** do not exert high effort  $e_H$  in human capital investment. They  
270 choose among three options:  $(n = 1, e = 0)$ ,  $(n = 1, e = e_L)$ , and  $(n = 0, e = e_L)$ ,<sup>7</sup>

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<sup>6</sup>The choice between  $(n = 0, e = e_H)$  and  $(n = 0, e = 0)$  does not depend on  $z$ . For  $e_H$  to be relevant,  $\lambda$  must be large enough so that  $(n = 0, e = e_H)$  is preferred to  $(n = 0, e = 0)$ . See Appendix A.2 for details on the lower bound for  $\lambda$ .

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

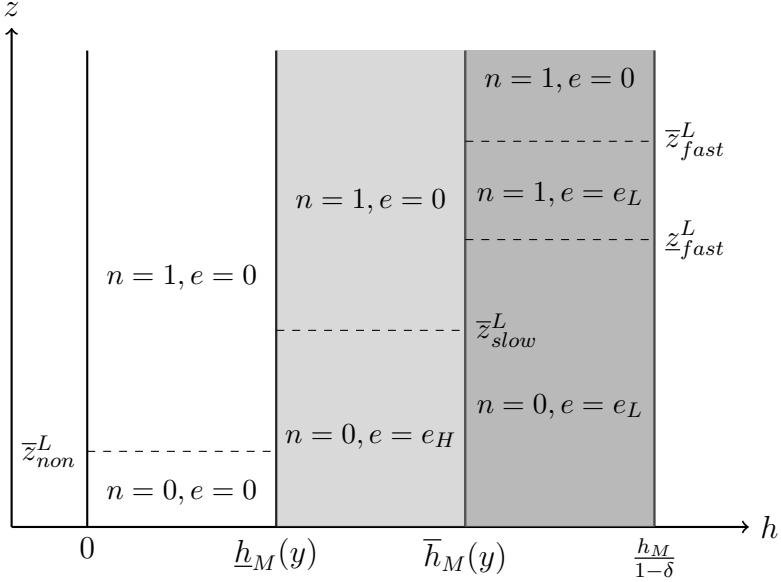


Figure 1: Decision Rule Diagram for  $0 \leq h < h_M(1 - \delta)^{-1}$

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  $0 \leq h < h_M \frac{1}{1-\delta}$ . 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  $z$ .

<sup>271</sup> with the decision rule as follows:

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

<sup>272</sup> where

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

<sup>273</sup>

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

<sup>274</sup> We set up our model so that  $\bar{z}_{fast}^L(a, h) > \underline{z}_{fast}^L(a, h)$ .<sup>8</sup>

<sup>275</sup> **Decision rule diagram:** Figure 1 illustrates how the decision rules of labor supply  
<sup>276</sup>  $n$  and human capital investment  $e$  vary with  $(z, h, a)$  for households with  $h < h_M \frac{1}{1-\delta}$   
<sup>277</sup> conditional on a given  $y$ . The human capital  $h$  changes along the horizontal axis

---

<sup>8</sup>Appendix A.2 provides the parameter restrictions such that the condition for  $(n = 0, e = e_H)$  to dominate  $(n = 0, e = 0)$  is sufficient for  $\bar{z}_{fast}^L(a, h) > \underline{z}_{fast}^L(a, h)$ .

278 and the labor productivity shock  $z$  changes along the vertical axis. The two vertical  
 279 lines  $\underline{h}_M(y)$  and  $\bar{h}_M(y)$  defined in (17) separate the state space into non-learners  
 280 (unshaded area), slow learners (lightly shaded area), and fast learners (darkly shaded  
 281 area). Within each learner type, labor supply and investment choices vary with  $z$   
 282 and the dashed horizontal lines represents the cutoffs in  $z$ .

283 Households with  $h_M \frac{1}{1-\delta} \leq h < h_H \frac{1}{1-\delta}$  have a decision rule analogous to those with  
 284  $h < h_M \frac{1}{1-\delta}$ . Conditional on  $y$ , the boundaries for learner type change to:

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

285 The four cutoffs in  $z$  that partition the decision regions change to  $\bar{z}_{non}^M(a, h)$ ,  $\bar{z}_{slow}^M(a, h)$ ,  
 286  $\underline{z}_{fast}^M(a, h)$ , and  $\bar{z}_{fast}^M(a, h)$  (see Appendix A.1 for the explicit formulae).

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

### 290 3.2 The Effects of Uninsured Idiosyncratic Risk

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

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

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

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

---

<sup>9</sup>The marginal effect of  $z'$  on  $\ln(c')$  is

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

309 gain of moving from  $h'$  to  $\bar{h}'$  is smaller due to the idiosyncratic risk. Human capital  
 310 investment is discouraged.

311 Taking into account endogenous labor supply reinforces the discouragement of  
 312 human capital investment by the idiosyncratic risk. Recall from Section 3.1.2 that  
 313 households with  $z'$  lower than a cutoff do not work. The endogenous labor supply  
 314 therefore provides insurance against the lower tail risk of the idiosyncratic  $z'$ . More-  
 315 over, the cutoff in  $z'$  is lower for those with higher human capital  $h'$ . This makes  
 316 households with higher  $h'$  more exposed to the lower tail risk than those with lower  
 317  $h'$ , further reducing the gain of human capital investment.

318 **Proposition 1.** *The uninsured idiosyncratic risk in  $z'$  makes households in period  
 319 1 save more, work more and invest less in human capital.*

### 320 3.3 Period-1 Saving and Human Capital Investment

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

326 When the optimal choice of human capital investment is zero, optimal saving is  
 327 identical in both scenarios. When the optimal human capital investment is either  $e_L$   
 328 or  $e_H$ , we compare the household's optimal saving to the case where human capital  
 329 investment is exogenously fixed at zero, i.e.,  $(n = 1, e = 0)$ .<sup>11</sup>

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

334 In particular, the household maximizes expected lifetime utility:

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

---

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.

<sup>10</sup>If depreciation is allowed, the analysis proceeds similarly but involves more comparison pairs.

<sup>11</sup>Why not compare to  $(n = 0, e = 0)$ ? Such a comparison is not meaningful when considering  $(n = 1, e = e_L)$  because the two scenarios involve different state spaces. To see it, suppose conditions are such that  $(n = 1, e = e_L)$  is optimal. If we were to fix  $e = 0$  exogenously, the household's lifetime income would fall, and as a result the household would have a greater incentive to work. Thus, it is not possible for the household to deviate from choosing  $n = 1$  when human capital is held fixed at  $e = 0$ . The comparison between  $(n = 0, e = 0)$  and  $(n = 0, e = e_L \text{ or } e_H)$  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.

<sup>335</sup> subject to the budget constraints

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

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

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

### <sup>336</sup> 3.3.1 Effect of on-job-training on saving

<sup>337</sup> We now compare the optimal saving between  $(n = 1, e = e_L)$  and  $(n = 1, e = 0)$ ,  
<sup>338</sup> where  $e_L$  allows households to move to a higher sector in period 2 with higher  
<sup>339</sup> sectoral productivity  $x(h')$ .

<sup>340</sup> To simplify the notation while maintaining the key economic forces, we normalize  
<sup>341</sup>  $(1 + r) = (1 + r') = 1$ ,  $w = w' = 1$ , the period-1 productivity shock  $z = 1$ , the  
<sup>342</sup> period-1 learning-ability shock  $y = 1$ , and the period-2 productivity shock  $z'$  to  
<sup>343</sup>  $\ln z' \sim \mathcal{N}(0, \sigma_z^2)$ . The budget constraints become:

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

<sup>344</sup> where  $x$  is the household's period-1 labor income that reflects both productivity and  
<sup>345</sup> skill.  $t \geq 1$  represents the effect of human capital investment on period-2 income:  
<sup>346</sup>  $t > 1$  if  $e = e_L$ ;  $t = 1$  if  $e = 0$ .

<sup>347</sup> The optimal saving is determined by the FOC:

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

<sup>348</sup> Denoting the mean and variance of  $z'$  as  $\mu$  and  $\Sigma$ , respectively:

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

<sup>349</sup> The second-order approximate solution to the FOC is:

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

<sup>350</sup> The first term is the *certainty-equivalent* saving, which reflects the consumption  
<sup>351</sup> smoothing motive, increasing in the period-1 resources  $a + x$  and decreasing in the  
<sup>352</sup> period-2 expected labor income  $tx\mu$ . The second term is the *precautionary* saving,  
<sup>353</sup> which is increasing in the variance of period-2 labor income  $t^2 x^2 \Sigma$  and decreasing in  
<sup>354</sup> the expected total resources  $a + x + tx\mu$ .

<sup>355</sup> The effect of on-job-training on saving can be decomposed into two components:

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

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

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

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

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

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

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

373 *Proof.* See Appendix B. □

### 374 3.3.2 Effect of full-time training on saving

375 We next compare the optimal saving between  $(n = 0, e = e_L \text{ or } e_H)$  and  $(n =$   
 376  $1, e = 0)$ . Note that full-time training requires the households to give up their labor  
 377 income in period 1, which is not the case for on-job-training. Following the same  
 378 normalization and notation as in the previous subsection, we can write the budget  
 379 constraints with full-time training and without training as:

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

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

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

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

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

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

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

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

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

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

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

389 **Lemma 1.** *If  $\frac{\Sigma}{\mu} < \hat{\sigma}(t)$ ,  $\Delta_H(x, a; t) < 0$  and decreases in  $x$ . If  $\frac{\Sigma}{\mu} > \bar{\sigma}(t)$ ,  $\Delta_H(x, a; t) >$   
 390 0 if and only if  $x > \hat{x}(a, t)$ ; moreover, for  $x > \hat{x}(a, t)$ ,  $\Delta_H(x, a; t)$  increases in  $x$ .*

391 *Proof.* See Appendix B. □

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

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

### 400 3.4 The Effects of an Anticipated Period-2 AI Shock

401 Suppose that an AI shock is anticipated to occur in period 2 and to increase the  
 402 labor productivity for the low sector and the high sector but not the middle sector.

<sup>403</sup> The effect of AI shock on the sectoral productivity is captured by  $\gamma$  with  $0 < \gamma < 1$ :

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

<sup>404</sup> In other words, the AI shock increases average labor productivity, reduces the earnings premium for the middle sector, and enlarges the earnings premium for the high sector relative to the middle sector.

### <sup>407</sup> 3.4.1 Effects on human capital investment

<sup>408</sup> The AI shock lowers the incentive to work in the middle sector in period 2. Consequently, households with  $h < h_M/(1 - \delta)$  reduce their human capital investment, while those with  $h > h_M/(1 - \delta)$  increase it. More specifically, the upper bounds that determine whether households undertake positive human capital investment – denoted by  $\bar{z}_{slow}^L$  and  $\bar{z}_{fast}^L$  for  $h < h_M/(1 - \delta)$ , and  $\bar{z}_{slow}^M$  and  $\bar{z}_{fast}^M$  for  $h > h_M/(1 - \delta)$  – respond in opposite directions to the anticipated shock: the former decrease with  $\gamma$  and the latter increase. This relationship is formalized below.

<sup>415</sup> **Proposition 4.** *An anticipated AI shock decreases human capital investment among households with  $h < h_M/(1 - \delta)$ , but increases it among those with  $h > h_M/(1 - \delta)$ . Specifically,  $\bar{z}_{slow}^L$  and  $\bar{z}_{fast}^L$  decrease with  $\gamma$ , while  $\bar{z}_{slow}^M$  and  $\bar{z}_{fast}^M$  increase with  $\gamma$ .*

<sup>418</sup> *Proof.* See Appendix B. □

### <sup>419</sup> 3.4.2 Effects on labor supply

<sup>420</sup> **via income:** The AI shock raises period-2 labor income for households who will work in the low or high sector, leading to a positive income effect that reduces their labor supply in period 1.

<sup>423</sup> **via full-time training:** Because full-time training and labor supply compete for time, the AI shock affects their tradeoff through its impact on human capital investment incentives. For  $h > h_M/(1 - \delta)$ , where AI makes investing in additional skills more attractive, households are more likely to engage in full-time training and thus reduce period-1 labor supply. In contrast, for  $h < h_M/(1 - \delta)$ , where the AI shock lowers the payoff to investing in skills, households shift away from full-time training and supply more labor in the first period.

### <sup>430</sup> 3.4.3 Effects on saving

<sup>431</sup> The AI shock increases sectoral labor productivity for the low and high sectors in period 2, while leaving the middle sector's labor productivity unchanged. Its effect

433 on saving can be analyzed as if we are varying the parameter  $t$  in the functions  
434  $\Delta_{\text{on-job}}(x, a; t)$ , defined in (33), and  $\Delta_H(x, a; t)$ , defined in (39).

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

- 436 • 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  $t' > t > 1$ .  
437 • 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  $1 > t' > t$ .

438 *Proof.* See Appendix B. □

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

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

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

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

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

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

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

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

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

### 477 3.5 *Limitations of the two-period model*

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

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

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

## 498 4 A Quantitative Model

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

Table I: Parameters for the Calibration

Parameter	Value	Description	Target or Reference
$\beta$	0.91795	Time discount factor	Annual interest rate
$\rho_z$	0.948	Persistence of $z$ shocks	Chang and Kim (2006)
$\sigma_z$	0.269	Standard deviation of $z$ shocks	Chang and Kim (2006)
$\underline{a}$	0	Borrowing limit	See text
$\chi_n$	2.47	Disutility from working	Employment rate
$\chi_e$	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
$\lambda$	0.2	Skill premium	Earnings Gini
$\delta_h$	0.1	HC depreciation rate	Standard value
$\alpha$	0.36	Capital income share	Standard value
$\delta$	0.1	Capital depreciation rate	Standard value

502    *4.1 Calibration*

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

507    The time discount factor,  $\beta$ , is calibrated to match an annual interest rate of 4  
 508    percent. We set  $\chi_n$  to replicate an 80 percent employment rate. We calibrate  $\chi_e$  to  
 509    match the fact that around 30 percent of the population invests in human capital  
 510    (OECD, 2025).

511    We calibrate parameters regarding labor productivity process as follows. We  
 512    assume that  $z$  follows the AR(1) process in logs:  $\log z' = \rho_z \log z + \epsilon_z$ , where  
 513     $\epsilon_z \sim N(0, \sigma_z^2)$ . The shock process is discretized using the Tauchen (1986) method,  
 514    resulting in a transition probability matrix with 11 grids. We set the persistence  
 515    parameter to  $\rho_z = 0.948$  and the standard deviation to  $\sigma_z = 0.269$ , following the  
 516    estimates reported in Chang and Kim (2006).

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

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

and high sectors are, respectively, 20, 40, and 40 percent. This population distribution roughly matches the fractions of U.S. workers in 2014 who are employed in routine manual occupations (low sector), routine cognitive and non-routine manual (middle sector), and non-routine cognitive (high sector) (Cortes *et al.*, 2017).

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

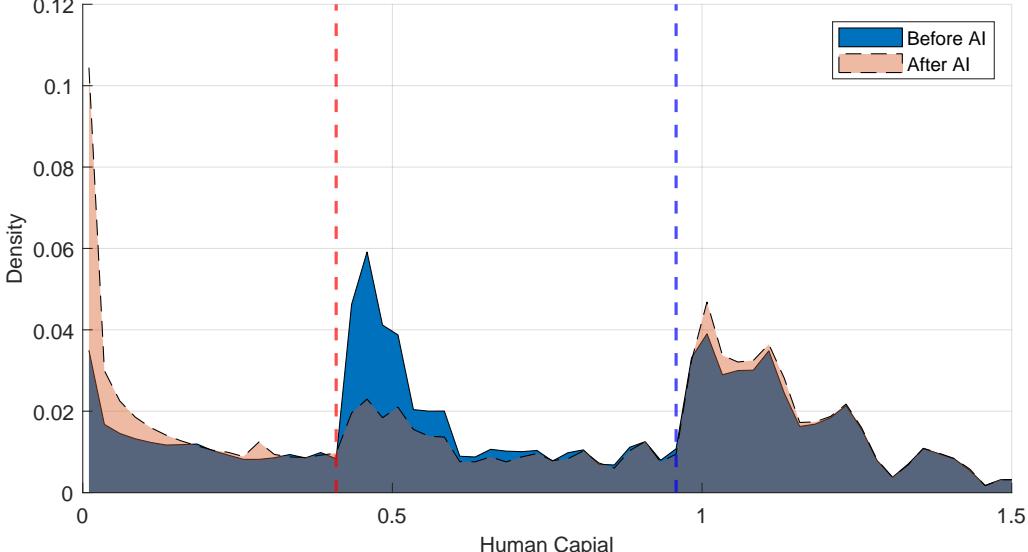
## 4.2 Key Moments: Data vs. Model

In Table II, we present a comparison of key moments between the model and the empirical data. The model does an excellent job of replicating the 80% employment rate observed in the data. In this context, employment is defined as having positive labor income in the given year, consistent with the common approach used in the literature. According to OECD (2025), the share of the population investing in human capital—those who are actively engaged in skill acquisition or education—is approximately 30%, a figure well matched by the model’s predictions. This is an important metric because it reflects the model’s capacity to capture the dynamics of human capital formation, which plays a critical role in shaping long-run earnings and income inequality. Additionally, the model accurately captures the distribution of income and earnings, aligning closely with observed data. This suggests that the model effectively incorporates the key mechanisms driving labor market outcomes and the corresponding distributional aspects of earnings. Although the model does not explicitly target the wealth Gini coefficient, it achieves a close match to the data: the empirical wealth Gini is 0.78, while the model produces a value of 0.76. This highlights the model’s ability to capture substantial wealth inequality in the economy.

## 4.3 Steady-state Distribution

Table III presents the steady-state distribution of population, employment, and assets across sectors. The population shares are calibrated to 20%, 40%, and 40% by adjusting the human capital thresholds that define sectors. The shares of employment and assets are endogenously determined by households’ labor supply

Figure 2: 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.

and savings decisions. Notably, the high sector accounts for 46% of total employment—exceeding its population share—indicating that a disproportionate number of households choose to work in that sector. Asset holdings are even more skewed: the high sector holds 68% of total assets, while the low sector holds only 8%.

Table III: Distribution of Population, Employment and Assets

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

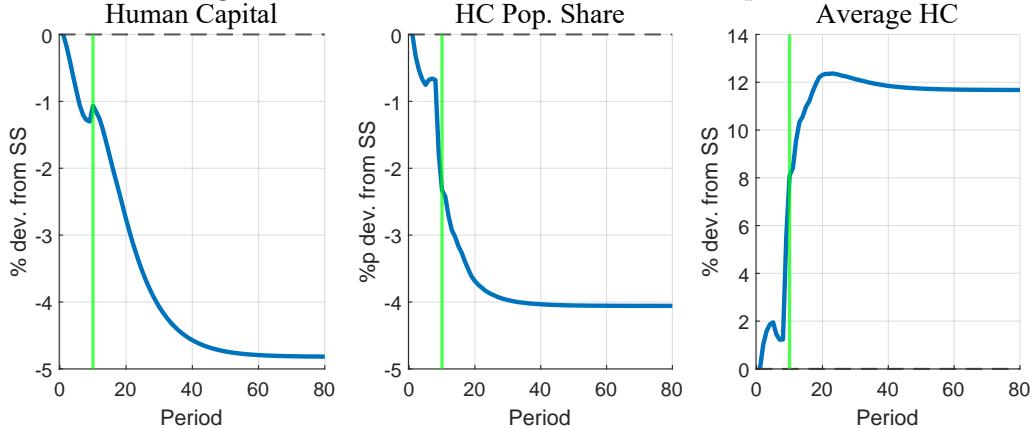
Note: Human capital cutoffs,  $h_H$  and  $h_M$ , determine the population share across sectors. Employment share and assets share are implied by households labor supply decisions and saving decisions.

## 5 AI's Impact on Human Capital Adjustments

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

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

Figure 3: 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.

### 571 5.1 Human Capital Adjustments

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

576 **Steady-state human capital distribution:** Figure 2 illustrates how households  
 577 reallocate across sectors in the new steady state relative to the initial one. The x-axis  
 578 denotes the level of human capital, while the y-axis indicates the mass of households  
 579 at each human capital level. The red vertical line marks the cutoff between the low  
 580 and middle sectors, and the blue vertical line marks the cutoff between the middle  
 581 and high sectors.

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

591 **Transition path** Figure 3 reports the transition dynamics of aggregate human  
 592 capital from the initial to the new steady state. The figure also displays its extensive  
 593 margin (the share of households making positive human capital investments) and  
 594 intensive margin (average human capital per household among those who invest).

595 As households reallocate from the middle sector to the low and high sectors, the

596 net effect is a gradual decline in aggregate human capital along the transition path.  
597 This mirrors the steady-state change observed in Figure 2, where the increased mass  
598 at the lower end of the low sector outweighs the increase in the high sector.

599 Additionally, human capital accumulation becomes increasingly concentrated  
600 among a smaller share of the population. The proportion of households making  
601 positive human capital investments steadily declines, ultimately stabilizing at a level  
602 4% lower than in the initial steady state. Meanwhile, the average human capital  
603 among those who invest rises, reaching a level 12% higher than the initial steady  
604 state in the long run.<sup>12</sup>

## 605 5.2 Job Polarization

606 An important implication of human capital adjustments to the AI shock is job  
607 polarization. Figure 4 illustrate the transition paths of population shares and em-  
608 ployment rates in each sector. Notably, the middle sector experiences a significant  
609 decline, with its population share decreasing by approximately 13%. Additionally,  
610 employment within this sector plummets to a level 16% lower than the initial steady  
611 state. In contrast, both the low and high sectors see increases in their population  
612 shares and employment rates. These dynamics indicate a reallocation of *workers*  
613 from the middle sector to the low and high sectors following the introduction of AI.

614 **Voluntary job polarization** This worker reallocation aligns with the phenomenon  
615 of “job polarization”(Goos *et al.*, 2014), where AI and automation technologies dis-  
616 proportionately replace tasks commonly performed by middle-skilled workers. How-  
617 ever, our model introduces a complementary mechanism to the conventional under-  
618 standing of this reallocation. Specifically, households in our model voluntarily exit  
619 the middle sector even before AI implementation by adjusting their human capital  
620 investments – many middle-sector workers opt for non-employment to invest in skills  
621 that will better position them for the post-AI labor market.<sup>13</sup> This mechanism is  
622 formally characterized in Proposition (4) in the two period model above.

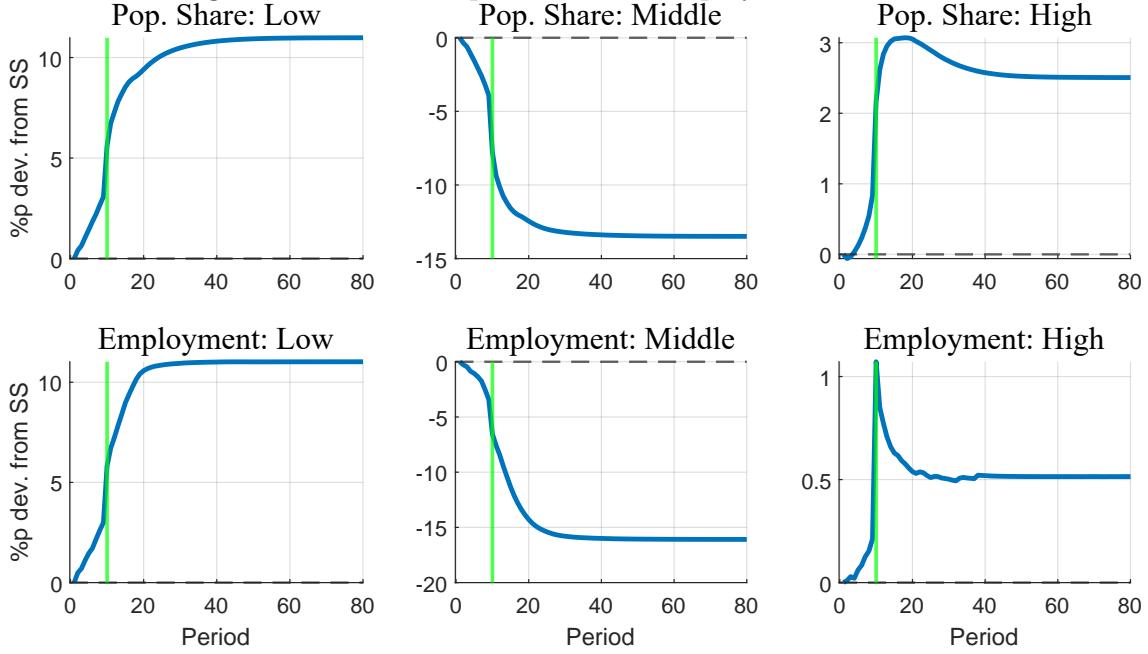
623 **Employment flows more towards the low sector** Another intriguing finding  
624 in our model is the more pronounced employment effect in the low sector compared  
625 to the high sector. In the new steady state, the employment rate in the low sector  
626 increases by 12%, whereas in the high sector,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

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

<sup>13</sup>To emphasize this key difference, our model deliberately abstracts from any direct negative effect of AI on middle-sector workers.

Figure 4: 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.

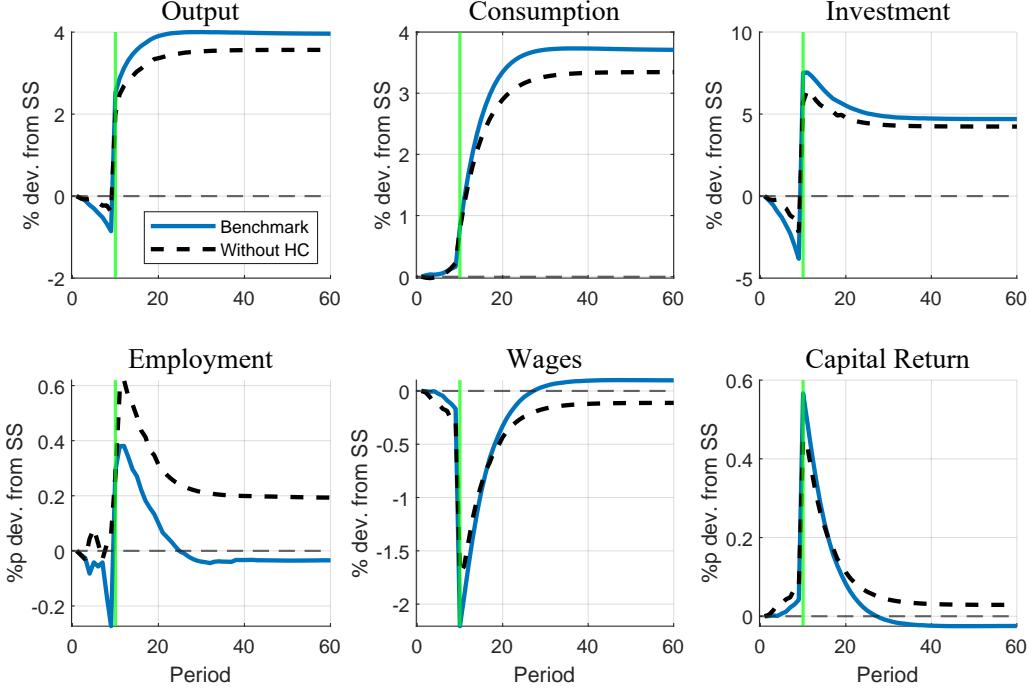
629 This disparity arises from two key factors. First, AI enhances the productivity of  
 630 low-sector workers by 7.5% and high-sector workers by 5%. However, this produc-  
 631 tivity differential alone does not fully account for the significant asymmetry. The  
 632 second factor is the variation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

## 639 6 The Aggregate and Distributional Effects of AI

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

647 These sectoral differences also induce human capital adjustments, as households  
 648 reallocate across sectors in response to changing incentives. This reallocation not

Figure 5: 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.

only shifts the distribution of labor productivity and aggregate productivity, but also directly shapes distributional outcomes, as households' relative positions in the income and asset distributions are altered by their movement across sectors.

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

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

667 *6.1 Aggregate Implications*

668 Figure 5 shows the transition paths of key macroeconomic variables—output, con-  
669 sumption, investment, and employment—as well as factor prices, including the wage  
670 rate and capital return. The blue solid lines depict results from the benchmark model  
671 with endogenous human capital adjustment, while the black dashed lines represent  
672 the No-HC model in which human capital is held fixed.

673 **6.1.1 AI's direct impacts**

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

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

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

693 **6.1.2 AI's indirect impacts via endogenous human capital adjustments**

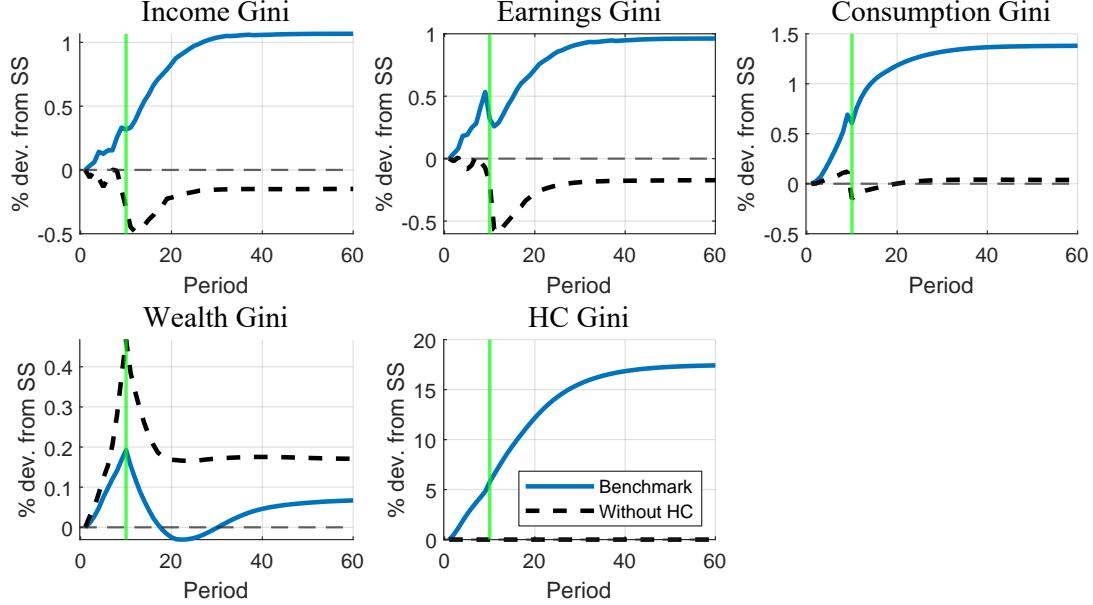
694 The difference between the No-HC model and the benchmark model captures the  
695 indirect effects of AI operating through endogenous human capital adjustments.  
696 Among all macroeconomic variables, this indirect effect is most pronounced for em-  
697 ployment.

698 In anticipation of AI, employment declines as some households temporarily exit  
699 the labor market to invest in human capital and prepare for the post-AI economy.<sup>14</sup>  
700 During this period, labor productivity remains unchanged, so the decline in em-  
701 ployment directly translates to a reduction in output. Consistent with standard

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<sup>14</sup>Empirical studies, such as Lerch (2021) and Faber *et al.*, (2022), support the short-term adverse effects of AI adoption on labor markets.

Figure 6: 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.

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 6 shows the transition paths of Gini coefficients for earnings (labor income), total income (capital and labor income), consumption, wealth (asset holdings), and human capital. The black dashed lines represent results from the No-HC

724 model, capturing the direct impact of AI without human capital adjustment. In  
725 contrast, the blue solid lines reflect the benchmark model, where human capital re-  
726 sponds endogenously to both anticipated and realized changes in the skill premium  
727 induced by AI.

### 728 6.2.1 Income, earnings, and consumption inequalities

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

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

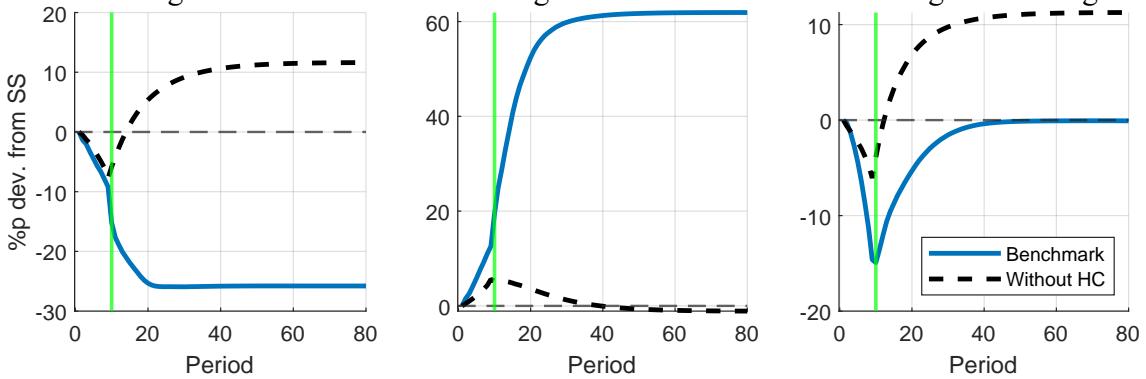
740 **Effects of AI-induced human capital adjustments:** Allowing human capital  
741 to adjust endogenously, however, leads to pronounced job polarization, as shown in  
742 Section 5.2. Households who would have qualified for middle-sector jobs now tran-  
743 sition to either the low or high sector.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

### 747 6.2.2 Wealth inequality

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

753 As discussed in Section 3.3, the effect of human capital investment on saving  
754 is theoretically ambiguous ex ante. On the one hand, higher expected future in-  
755 come from on-the-job and full-time training tends to crowd out saving through the  
756 standard consumption-smoothing motive. On the other hand, greater exposure to  
757 idiosyncratic risk strengthens the precautionary saving motive and can crowd in sav-  
758 ing. Propositions 2 and 3 demonstrate that, when idiosyncratic risk is sufficiently  
759 large, human capital investment crowds out saving for low-labor-income households

Figure 7: 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.

760 but crowds in saving for high-labor-income households. As labor income is positively  
 761 affected by households productivity, the net effect of human capital investment on  
 762 saving is positive precisely for the more productive households.

763 In our quantitative model, this mechanism shows up most clearly in the middle  
 764 sector. Figure 7 plots the transition of average assets by sector in the benchmark  
 765 economy and in the counterfactual No HC economy. “Average Asset” is defined as  
 766 total assets held by households in a given sector divided by that sector’s popula-  
 767 tion share, so it reflects both within-sector saving behavior and the composition of  
 768 households across sectors.

769 **AI’s direct impacts:** Without any human capital adjustment, AI’s impact on  
 770 households’ saving works purely through income effect. In both the low and high  
 771 sectors, households reduce their savings in anticipation of AI, expecting higher life-  
 772 time labor income. After AI is implemented at period 10, their savings increase  
 773 alongside rising labor incomes. In contrast, households in the middle sector, antici-  
 774 pating a negative income effect from AI due to a lower wage rate, increase their  
 775 savings prior to period 10. Once AI is introduced and the wage rate recovers,  
 776 middle-sector households reduce their savings.

777 **Effects of AI-induced human capital adjustments:** Endogenous human cap-  
 778 ital responses introduce an additional channel. Relative to the No-HC model, the  
 779 benchmark exhibits a pronounced increase in average assets in the middle sector.<sup>15</sup>  
 780 Middle-sector households are relatively productive in our model, and a composi-

<sup>15</sup>In the benchmark model, average assets in the high sector decline due to a composition effect, as relatively low-wealth households move up from the middle sector. In the low sector, average assets also fall, primarily because the scope for precautionary saving is limited, and this effect is reinforced by composition changes.

tion effect further amplifies their asset accumulation: many less productive middle-sector households endogenously move down to the low sector, so the remaining middle-sector population is positively selected on productivity.<sup>16</sup> In addition, as discussed above, some middle-sector households voluntarily exit employment to invest in human capital full-time. Taken together, these households are the “active training” and relatively high-productivity workers in our model; thus, as predicted by Propositions 2 and 3, their human capital investment tends to crowd in saving. Accordingly, AI-induced human capital adjustment strengthens asset accumulation in the middle of the distribution and compresses the gap between the middle and the top. Quantitatively, the increase in wealth inequality in the benchmark economy with endogenous human capital is therefore markedly smaller than in the No HC economy, highlighting the stabilizing role of human capital adjustment in the wealth distribution.

## 7 Conclusion

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

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

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<sup>16</sup>Note that the share of households moving up is relatively small.

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## 909 A Household Decision Rule Cutoffs

### 910 A.1 Additional cutoffs formulae for households

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

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

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

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

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

### 911 A.2 Parameter restrictions for cutoffs ranking

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

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

914 or equivalently:

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

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

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

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

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

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

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

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

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

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

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

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

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

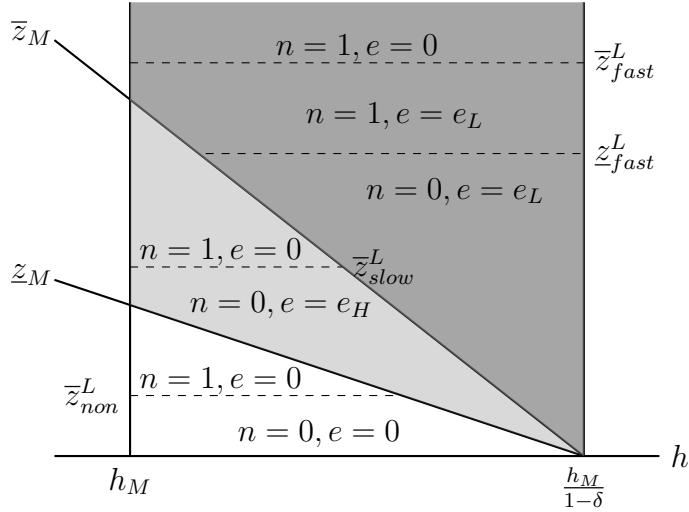


Figure A.1: Decision Rule Diagram for  $h_M \leq h < h_M(1 - \delta)^{-1}$

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

<sup>926</sup> Evaluating the left-hand-side at  $z = \underline{z}_{fast}$  yields:

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

<sup>927</sup> We have that  $\underline{\lambda}_1 > \underline{\lambda}_2$  and  $\underline{\lambda}_3 > \underline{\lambda}_4$  if

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

<sup>928</sup> Therefore, the inequality above implies that the conditions (A.6) and (A.7) are  
<sup>929</sup> sufficient for the conditions (A.11) and (A.12). Furthermore,  $\lambda_3 \geq \lambda_1$  so that the  
<sup>930</sup> condition (A.7) is sufficient for the condition (A.6).

<sup>931</sup> We can then conclude that the conditions (A.7) and (A.13) are sufficient for  
<sup>932</sup> 1) the slower learners always prefers  $(n = 0, e = e_H)$  over  $(n = 0, e = 0)$ , and 2)  
<sup>933</sup>  $\bar{z}_{fast} > \underline{z}_{fast}$ , i.e., there exists state space where  $(n = 1, e = e_L)$  is optimal.

### <sup>934</sup> A.3 Labor supply and human capital investment when $y$ perfectly cor- <sup>935</sup> relates with $z$

<sup>936</sup> When the learning ability  $y$  is perfectly correlated with the idiosyncratic productivity  
<sup>937</sup>  $z$ , the decision rule  $(n, e)$  is a function of states  $(z, h, a)$  instead of  $(z, h, a, y)$ .

<sup>938</sup> Figure A.1 illustrates the decision rule  $(n, e)$  for households with  $h_M \leq h <$

939  $h_M \frac{1}{1-\delta}$ . The human capital  $h$  changes along the horizontal line and the idiosyncratic  
 940 productivity  $z$  changes along the vertical line. The two diagonal lines,  $\bar{z}_M(h)$  and  
 941  $\underline{z}_M(h)$  are defined as:

$$\underline{z}_M(h) := \frac{h_M - (1 - \delta)h}{e_H}; \quad \bar{z}_M(h) := \frac{h_M - (1 - \delta)h}{e_L} \quad (\text{A.14})$$

942 They separate the state space into three areas: the unshaded area represents the  
 943 non-learners, the lightly-shaded area represents the slow learners, and the darkly-  
 944 shaded area represents the fast learners. The areas are divided by dashed horizontal  
 945 lines associated with cutoffs  $\bar{z}_{non}^L(a)$ ,  $\bar{z}_{slow}^L(a)$ ,  $\underline{z}_{fast}^L(a)$ , and  $\bar{z}_{fast}^L(a)$  defined in (18),  
 946 (19), (22), and (21).

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

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

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

$$\underline{z}_H(h) := \frac{h_H - (1 - \delta)h}{e_H}; \quad \bar{z}_H(h) := \frac{h_H - (1 - \delta)h}{e_L} \quad (\text{A.15})$$

956 The four cutoffs of  $z$  are  $\bar{z}_{non}^M$ ,  $\bar{z}_{slow}^M$ ,  $\underline{z}_{fast}^M$ , and  $\bar{z}_{fast}^M$  defined in Appendix A.1  
 957 Households with  $h \geq h_H \frac{1}{1-\delta}$  are non-learners, and have their decision exactly  
 958 the same as in the benchmark model.

## 959 B Proof of Proposition

### 960 B.1 Proof of Proposition 2

961 The derivative of saving with respect to  $t$  is

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

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

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

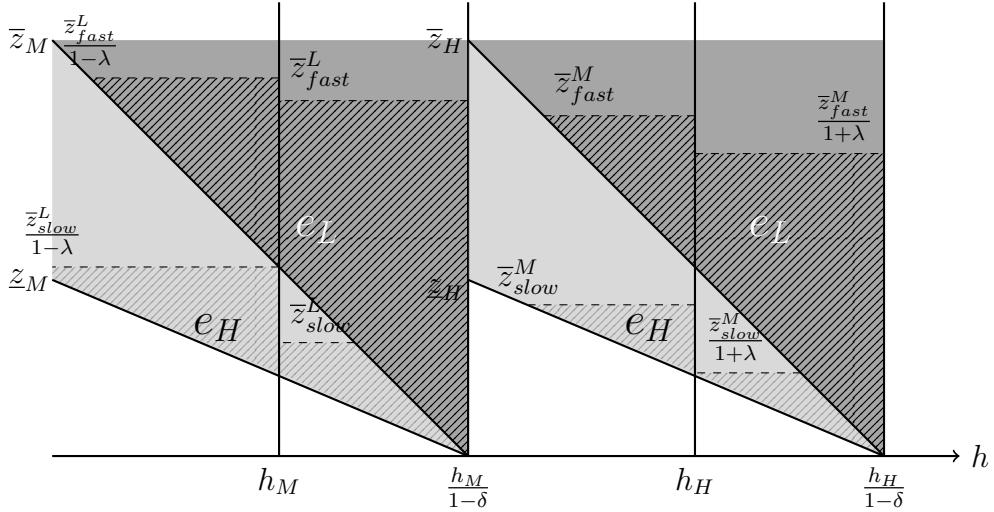


Figure A.2: State Space for Human Capital Investment

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

963 Define

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

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

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

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

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

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

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

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

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

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

971 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

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

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

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

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

975 *B.2 Proof of Lemma 1*

976 Denote

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

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

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

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

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

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

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

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

981

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

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

983 If

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

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

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

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

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

987 If

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

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

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

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

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

### 990 *B.3 Proof of Proposition 4*

991 The relevant upper bounds of  $z$  for positive human capital investment are functions  
992 of  $\gamma$  (to the first order approximation):

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

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

### 995 *B.4 Proof of Proposition 5*

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

996 differentiating with respect to  $t$  gives

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

997 Since

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

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

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

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

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

1000 so  $G(x, a; t)$  is strictly increasing in  $t$ , and so is  $\Delta_H(x, a; t)$ .

1001 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

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

1003 so  $f'(t) > 0$ , i.e.  $f(t)$  is strictly increasing in  $t$ .

1004 **Case 1:**  $1 < t < t'$

1005 Suppose  $\Delta_{\text{on-job}}(x, a; t) > 0$ . Then

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

1006 Since  $f$  is increasing,

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

1007 which implies

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

1008 Because  $t > 1$ , the inequality  $\Delta_{\text{on-job}}(x, a; t) > 0$  forces  $f(t) > 0$ .

1009 Now for any  $t' > t$ ,

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

1010 and therefore

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

1011 We then have that:

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

1012 That is, once  $\Delta_{\text{on-job}}(x, a; t)$  becomes positive for  $t > 1$ , it is strictly increasing in  $t$  thereafter.

1014 **Case 2:**  $t < t' < 1$

1015 For  $t < 1$ ,

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

1016 Suppose  $\Delta_{\text{on-job}}(x, a; t) > 0$ . Then

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

1017 Since  $f$  is increasing

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

1018 which implies

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

1019 Because  $t < 1$ , the inequality  $\Delta_{\text{on-job}}(x, a; t) > 0$  forces  $f(t) < 0$ .

1020 Consider

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

1021 If  $f(u) < 0$  for all  $u \in [t, t']$ , then  $\int_t^{t'} f(u) du < 0$ .

1022 If there exists some  $t_s \in [t, t']$  such that  $f(t_s) = 0$ , so  $f(u) < 0$  for  $u < t_s$  and  
1023  $f(u) > 0$  for  $u > t_s$ . Then  $f(u) > 0$  for  $u \in [t', 1]$ . Hence,

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

1024 This implies that

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

1025 Together with the inequality  $\Delta_{\text{on-job}}(x, a; t) > 0$ , we have that

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

1026 We then have that

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

1027 Thus, for  $t < 1$ , whenever  $\Delta_{\text{on-job}}(x, a; t) > 0$ , increasing  $t$  toward 0 makes  $\Delta_{\text{on-job}}$   
1028 strictly decrease.

## 1029 C Computational Procedure for the Quantitative Model

### 1030 C.1 Steady-state Equilibrium

1031 In the steady-state, the measure of households,  $\mu(a, h, z)$ , and the factor prices are  
1032 time-invariant. We find a time-invariant distribution  $\mu$ . We compute the house-  
1033 holds' value functions and the decisions rules, and the time-invariant measure of the  
1034 households. We take the following steps:

- 1035 1. We choose the number of grid for the risk-free asset,  $a$ , human capital,  $h$ , and

1036 the idiosyncratic labor productivity,  $z$ . We set  $N_a = 151$ ,  $N_h = 151$ , and  
 1037  $N_z = 9$  where  $N$  denotes the number of grid for each variable. To better  
 1038 incorporate the saving decisions of households near the borrowing constraint,  
 1039 we assign more points to the lower range of the asset and human capital.

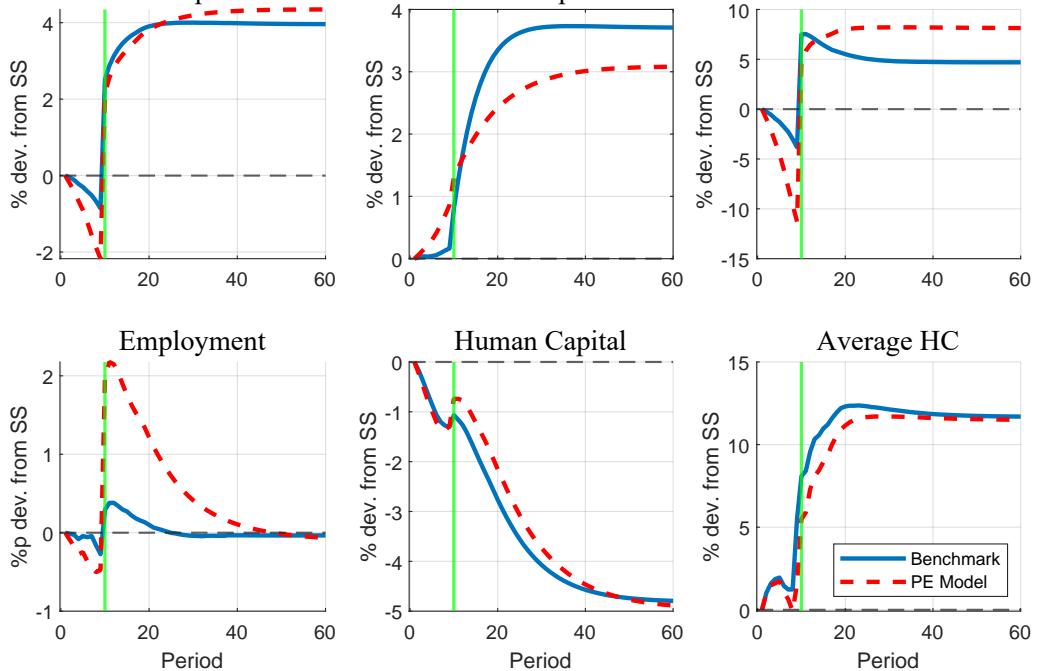
- 1040 2. Productivity  $z$  is equally distributed on the range  $[-3\sigma_z/\sqrt{1-\rho_z^2}]$ . As shown  
 1041 in the paper, we construct the transition probability matrix  $\pi(z'|z)$  of the  
 1042 idiosyncratic labor productivity.
- 1043 3. Given the values of parameters, we find the value functions for each state  
 1044  $(a, h, z)$ . We also obtain the decision rules: savings  $a'(a, h, z)$ , and  $h'(a, h, z)$ .  
 1045 The computation steps are as follow:
- 1046 4. After obtaining the value functions and the decision rules, we compute the  
 1047 time-invariant distribution  $\mu(a, h, z)$ .
- 1048 5. If the variables of interest are close to the targeted values, we have found the  
 1049 steady-state. If not, we choose the new parameters and redo the above steps.

## 1050 C.2 Transition Dynamics

1051 We incorporate the transition path from the status quo to the new steady state. We  
 1052 describe the steps below.

- 1053 1. We obtain the initial steady state and the new steady state.
- 1054 2. We assume that the economy arrives at the new steady state at time  $T$ . We  
 1055 set the  $T$  to 100. The unit of time is a year.
- 1056 3. We initialize the capital-labor ratio  $\{K_t/L_t\}_{t=2}^{T-1}$  and obtain the associated  
 1057 factor prices  $\{r_t, w_t\}_{t=2}^{T-1}$ .
- 1058 4. As we know the value functions at time  $T$ , we can obtain the value functions  
 1059 and the decision rules in the transition path from  $t = T - 1$  to 1.
- 1060 5. We compute the measures  $\{\mu_t\}_{t=2}^T$  with the measures at the initial steady state  
 1061 and the decision rules in the transition path.
- 1062 6. We obtain the aggregate variables in the transition path with the decision rules  
 1063 and the distribution measures.
- 1064 7. We compare the assumed paths of capital and the effective labor with the  
 1065 updated ones. If the absolute difference between them in each period is close  
 1066 enough, we obtain the converged transition path. Otherwise, we assume new  
 1067 capital-labor ratio and go back to 3.

Figure D.1: 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.

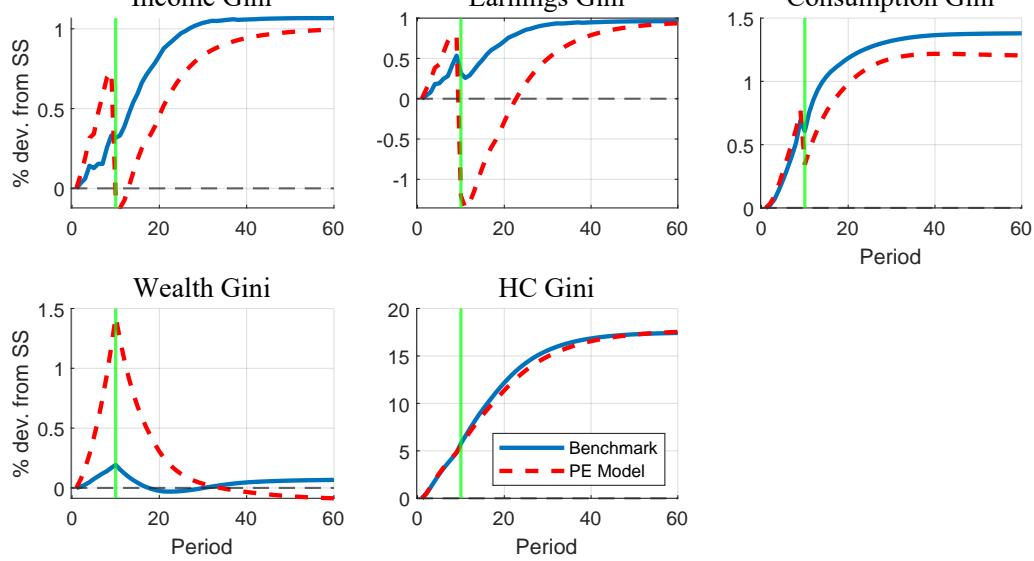
## 1068 D Investigating the GE channel of AI's impact

1069 Figures D.1 and D.2 compare the transition dynamics in the benchmark general-  
 1070 equilibrium model with those in a partial-equilibrium (PE) version of the model,  
 1071 where individual behavior responds to AI adoption but factor prices are held fixed  
 1072 at their initial steady-state values. The green vertical line marks the date of AI  
 1073 adoption.

1074 On the aggregate side (Figure D.1), both models deliver a long-run expansion  
 1075 in output, consumption, and investment after AI adoption. In the PE model, GDP  
 1076 responses are quite similar across the two models, but the composition of that re-  
 1077 sponse differs. In the PE model, consumption rises by less, while investment rises  
 1078 by more in the long run. The reason is that, in the benchmark, the long-run re-  
 1079 turn on capital becomes negative (as shown in Figure 5), whereas in the PE model  
 1080 there is no such price effect. As a result, households in the PE environment have  
 1081 stronger incentives to save and invest, tilting the response toward investment rather  
 1082 than consumption. Even though aggregate human-capital dynamics do not differ  
 1083 much across the two environments, employment behaves very differently around the  
 1084 adoption date. In the PE model, employment rises sharply when AI is introduced  
 1085 because wages do not fall as employment increases.

1086 Turning to inequality dynamics (Figure D.2), the long-run behavior is similar  
 1087 across the two environments, but the impact responses differ markedly. As noted  
 1088 above, employment rises more on impact in the PE model even though output re-

Figure D.2: 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.

1089 responses are similar. This implies that the additional employment mainly comes from  
 1090 low-productivity households. Consequently, the Gini coefficients for income, earn-  
 1091 ings, and consumption fall more on impact in the PE model but then move toward  
 1092 levels similar to those in the benchmark once job polarization and skill reallocation  
 1093 take hold. The human-capital Gini shows virtually no difference between the two  
 1094 models. By contrast, the wealth Gini exhibits very different transition dynamics.  
 1095 In the PE model, it displays a pronounced but short-lived spike early in the transi-  
 1096 tion because poor households save less, as wages do not fall there in response to AI  
 1097 adoption, unlike in the benchmark economy. In the long run, however, the wealth  
 1098 Gini converges to a level similar to the benchmark, mainly because middle-sector  
 1099 households gradually increase their savings, as discussed in the main text.