

AI and Human Capital Accumulation: Aggregate and Distributional Implications*

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Abstract

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

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¹ 1 Introduction

² The distinctive nature of AI advancements lies in their ability to perform cognitive,
³ non-routine tasks that previously required significant education and expertise, fun-
⁴ damentally differentiating its impact on the labor market and economy from that
⁵ of general automation. For example, AI tools in medical diagnostics now assist ra-
⁶ diologists in analyzing medical images, potentially reducing demand for entry-level
⁷ radiologists while simultaneously increasing the productivity of senior professionals.
⁸ More generally, AI could shift the premium associated with various skills levels, de-
⁹ valuing middle-level skills while increasing the demand for high-level expertise. In
¹⁰ anticipation of these changes, households are likely to adjust their human capital
¹¹ investments.

¹² According to the National Center for Education Statistic,¹ college enrollment in
¹³ the U.S. has been declining since 2010. The National Student Clearinghouse Re-
¹⁴ search Center reports that the undergraduate college enrollment decline has acceler-
¹⁵ ated since the pandemic began, resulting in a loss of almost 6% of total enrollment
¹⁶ between fall 2019 to fall 2023, while graduate enrollment has risen by about 5%.²
¹⁷ These shifts, regardless of their causes, highlight evolving patterns in human capital
¹⁸ investment.

¹⁹ This paper develops a model to study the effects of AI advancements on human
²⁰ capital investment and their subsequent impact on aggregate and distributional
²¹ outcomes of the economy. We posit an economy consisting of three sectors, requiring
²² low, middle and high levels of skill (human capital) with increasing sectoral labor
²³ productivity. Households can invest in their human capital to move up to more
²⁴ productive sectors. But if they do not invest, their human capital depreciates and,
²⁵ over time, they will move down to less productive sectors. We model human capital
²⁶ investment at two levels, a low level attainable on the job and a high level requiring
²⁷ full-time commitment, such as pursuing higher education. Households are subject
²⁸ to uninsurable idiosyncratic risk in terms of productivity shocks that affect both
²⁹ labor productivity and effectiveness in human capital investment.

³⁰ The interaction between human capital investment and labor supply presents a
³¹ tradeoff at the household level between current wage earning and future wage gains.
³² At aggregate level, the interaction implies that when individuals transition from
³³ the middle to the high sector, they may temporarily exit the workforce to upskill,
³⁴ reducing immediate labor supply but improving future labor productivity.

³⁵ We model AI advancements as increasing the productivity for the low and high
³⁶ sectors but not for the middle sector so that the skill premium of the middle sector
³⁷ decreases and the skill premium of the high sector increases. Allowing for human

¹https://nces.ed.gov/programs/digest/d22/tables/dt22_303.70.asp

²<https://public.tableau.com/app/profile/researchcenter/viz/CTEEFall2023dashboard/CTEEFall2023>

38 capital adjustments not only alters AI's economic implications quantitatively, it also
39 makes a qualitative difference.

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

45 Using a two-period model, we show how households' labor supply and human
46 capital investment are affected by their productivity shocks, asset holdings and
47 stocks of human capital. The effects of AI, in this partial equilibrium analysis, are
48 shown to discourage human capital investment for households in the low sector and
49 encourage human capital investment for households in the middle sector, thereby
50 increasing human capital inequality. In addition, AI worsens consumption inequality
51 for households with low levels of human capital and reduces consumption inequality
52 for those with high levels of human capital.

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

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

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

76 Our findings reveal that human capital responses to AI amplify its positive effects
77 on aggregate output and consumption, mitigate the AI-induced rise in precautionary

78 savings, and stabilize the adjustments in wages and asset returns. Furthermore,
79 while AI-driven human capital adjustments increase inequalities in income, earnings,
80 and consumption, they unexpectedly reduce wealth inequality. We also show that
81 the redistribution channel is the dominant factor in the effects of human capital
82 adjustments, whereas the general equilibrium channel, via wage and capital return
83 changes, plays a comparatively minor role.

84 INTRODUCING PRECAUTIONARY SAVING MOTIVE IN THE WAGE PO-
85 LARIZATION INVESTIGATION Autor *et al.*, (2006)

86 This paper relates to the literature examining how technological advancements,
87 including AI, have significantly contributed to job polarization. Goos and Manning
88 (2007) show that since 1975, the United Kingdom has experienced job polarization,
89 with increasing employment shares in both high- and low-wage occupations. Autor
90 and Dorn (2013) expanded on this by providing a unified analysis of the growth of
91 low-skill service occupations, highlighting key factors that amplify polarization in
92 the U.S. labor market. Empirical evidence from Goos *et al.*, (2014) further confirms
93 pervasive job polarization across 16 advanced Western European economies. In the
94 U.S., Acemoglu and Restrepo (2020) show that robots can reduce employment and
95 wages, finding robust negative effects of automation on both in various commuting
96 zones.

97 The introduction of AI and robotics has had adverse effects on labor markets,
98 with significant implications for employment and labor force participation. Lerch
99 (2021) highlights that the increasing use of robots not only displaces workers but
100 also negatively impacts overall labor force participation rates. Similarly, Faber *et al.*,
101 (2022) demonstrate that the detrimental effects of robots on the labor market have
102 resulted in a decline in job opportunities, particularly in sectors where automation
103 is prevalent. These findings suggest that while technological advancements bring
104 productivity gains, they simultaneously reduce employment prospects and partici-
105 pation in the labor market, exacerbating economic challenges for certain groups of
106 workers.

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

118 The response of human capital accumulation to technological disruption could
119 also go to the other extreme. A 2022 report by Higher Education Strategy Associates
120 finds that following decades of growth, dropping student enrollment has become a
121 major trend in higher education in the Global North.³ In the U.S., the public across
122 the political spectrum has increasingly lost confidence in the economic benefits of
123 a college degree. Pew Research Center reports that about half of Americans say
124 having a college degree is less important today than it was 20 years ago in a survey
125 conducted in 2023.⁴ A 2022 study from Public Agenda, a nonpartisan research
126 organization, shows that young Americans without college degrees are most skeptical
127 about the value of higher education.

128 The rise of AI and automation also plays a significant role in exacerbating gen-
129 eral inequality, particularly through its impact on education and wealth distribution.
130 Prettner and Strulik (2020) present a model showing that innovation-driven growth
131 leads to an increasing proportion of college graduates, which in turn drives higher
132 income and wealth inequality. As technology advances, workers with higher educa-
133 tional attainment benefit disproportionately, widening the gap between those with
134 and without advanced skills. Sachs and Kotlikoff (2012) also explore this dynamic,
135 providing a model within an overlapping generations framework that examines the
136 interaction between automation and education. They demonstrate how automation
137 can further entrench inequality by favoring workers with higher levels of educa-
138 tion, as those without adequate skills are more likely to be displaced or see their
139 wages stagnate. This interaction between technological change and educational at-
140 tainment not only amplifies economic inequality but also perpetuates disparities in
141 wealth across generations.

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

150 2 Model Environment

151 Time is discrete and infinite. There is a continuum of households. Each household
152 is endowed with one unit of indivisible labor and faces idiosyncratic productivity

³<https://higheredstrategy.com/world-higher-education-institutions-students-and-funding/>

⁴<https://www.pewresearch.org/social-trends/2024/05/23/public-views-on-the-value-of-a-college-degree/>

¹⁵³ shock, z , that follows an AR(1) process in logs:

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

¹⁵⁴ The asset market is incomplete following Aiyagari (1994), and the physical capital,
¹⁵⁵ a , is the only asset available to households to insure against this idiosyncratic risk.
¹⁵⁶ Households can also invest in human capital, h , which allows them to work in sectors
¹⁵⁷ with different human capital requirement.

¹⁵⁸ 2.1 Production Technology

¹⁵⁹ The production technology in the economy is a constant-returns-to-scale Cobb-
¹⁶⁰ Douglas production function:

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

¹⁶¹ K is the aggregation of all physical capital held by the households. L is the aggre-
¹⁶² gation of effective labor supplied by the households and employed in three sectors:
¹⁶³ low, middle, and high.

¹⁶⁴ These sectors differ in their technologies for converting labor into effective labor
¹⁶⁵ units and in the levels of human capital required for employment. The middle sector
¹⁶⁶ employs households with human capital above h_M and converts one unit of labor
¹⁶⁷ to one effective labor unit. The high sector, requiring human capital above h_H ,
¹⁶⁸ converts one unit of labor to $1 + \lambda$ effective units, while the low sector, with no
¹⁶⁹ human capital requirement, converts one unit into $1 - \lambda$ effective units. This implies
¹⁷⁰ a sectoral labor productivity $x(h)$ that is a step function in human capital:

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

¹⁷¹ A household i who decides to work thus contributes $z_i x(h_i)$ units of effective labor,
¹⁷² where z_i is his idiosyncratic productivity. Denote $n_i \in \{0, 1\}$ as the indicator that
¹⁷³ takes one if the household works and zero if the household does not. The aggregate
¹⁷⁴ labor is

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

¹⁷⁵ assuming perfect substitutability of effective labor across the three sectors.

¹⁷⁶ 2.2 Household's Problem

¹⁷⁷ Households derive utility from consumption, incur disutility from labor and effort of
¹⁷⁸ human capital investment. A household maximizes the expected lifetime utility by

¹⁷⁹ optimally choosing consumption, saving, labor supply and human capital investment
¹⁸⁰ each period, based on his idiosyncratic productivity shock z_t :

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

¹⁸¹ where c_t represents consumption, a_{t+1} represents saving, $n_t \in \{0, 1\}$ is labor supply,
¹⁸² and e_t is the effort of human capital investment.

¹⁸³ If a household decides to work in period t , he will be employed into the appropriate sector according to his human capital h_t and receive labor income $w_t z_t x(h_t)$,
¹⁸⁴ where w_t is the economy-wide wage rate of effective labor unit.
¹⁸⁵

¹⁸⁶ Denote r_t as the interest rate on the physical capital a_t . The household's budget
¹⁸⁷ constraint is

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

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

¹⁸⁸ We prohibit households from borrowing $a_{t+1} \geq 0$ to simplify analysis.⁵

¹⁸⁹ Human capital investment can take three levels of effort: $\{0, e_L, e_H\}$. A non-
¹⁹⁰ working household is free to choose any of the three effort levels but a working
¹⁹¹ household cannot devote the highest level of effort e_H , reflecting a trade-off between
¹⁹² working and human capital investment. Hence:

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

¹⁹³ Its contribution to next-period human capital is subject to the productivity shock:

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

¹⁹⁴ where δ is human capital's depreciation rate.

¹⁹⁵ 3 Household Decisions in a Two-Period Model

¹⁹⁶ In this section, we solve the household's problem with two periods to gain intuition.

¹⁹⁷ **Period-2 decisions** Households do not invest in human capital or physical capital
¹⁹⁸ in the last period. The only relevant decision is whether to work.

¹⁹⁹ The household works $n = 1$ if and only if $z \geq \bar{z}(h, a)$, with $\bar{z}(h, a)$ defined as

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

⁵ According to Aiyagari (1994), a borrowing constraint is necessarily implied by present value budget balance and nonnegativity of consumption. Since the borrowing limit is not essential to our analysis, we set it to zero for simplicity.

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

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

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

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

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

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

217 3.1 Period-1 Labor Supply and Human Capital Investment

218 3.1.1 Consumption and saving without uncertainty

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

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

222 The log utility in consumption implies the optimality condition:

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

²²³ Combining it with the budget constraint, we obtain the optimal consumption as a
²²⁴ function of labor supply n and human capital investment e :

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

²²⁵ 3.1.2 Labor supply and human capital investment

²²⁶ The optimal consumption rules in (14) and (13) allow us to express the household's
²²⁷ problem as the maximization of an objective function in labor supply n and human
²²⁸ capital investment e :⁶

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

²²⁹ This maximization depends critically on the household's current human capital and
²³⁰ achievable next-period human capital. Accordingly, we partition households into
²³¹ five ranges of h : $[0, h_M]$, $[h_M, h_M(1 - \delta)^{-1}]$, $[h_M(1 - \delta)^{-1}, h_H]$, $[h_H, h_H(1 - \delta)^{-1}]$,
²³² and $[h_H(1 - \delta)^{-1}, h_{\max}]$.

²³³ We now derive the decision rules for households $h \in [h_M, h_M(1 - \delta)^{-1}]$ in detail,
²³⁴ as the decision rules for the other four ranges are similar. For households with
²³⁵ $h < h_M(1 - \delta)^{-1}$, we define two cutoffs in z :

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

²³⁶ These cutoffs divide households into three groups based on their ability to be em-
²³⁷ ployed in the middle sector in the next period.

²³⁸ **Non-learners** are households with $z < \underline{z}_M(h)$. They cannot achieve $h' > h_M$
²³⁹ with either e_L or e_H level of human capital investment today. As a result, they will
²⁴⁰ choose not to invest in human capital, $e = 0$, and their future sectoral productivity
²⁴¹ will be $x(h') = 1 - \lambda$. These non-learners work $n = 1$ if and only if $z \geq \bar{z}_{non}^L(a)$:

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

²⁴² **Slow learners** are households with $z \in (\underline{z}_M(h), \bar{z}_M(h))$. These households can
²⁴³ reach $h' > h_M$ in the next period only by investing $e = e_H$ today. Their choice
²⁴⁴ is restricted to $e = 0$ or $e = e_H$, since selecting $e = e_L$ incurs a cost without any
²⁴⁵ future benefit. Slow learners must trade off between working and human capital
²⁴⁶ investment: choosing $e = e_H$ requires not working today ($n = 0$), while opting to

⁶This follows since $c' = \beta(1 + r')c$, so $\ln c' = \ln \beta + \ln(1 + r') + \ln c$.

²⁴⁷ work means forgoing investment in human capital ($n = 1, e = 0$).⁷

²⁴⁸ Slow learners prefer ($n = 1, e = 0$) to ($n = 0, e = e_H$) if and only if $z \geq \bar{z}_{slow}^L(a)$:

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

²⁴⁹ **Fast learners** are households with $z > \bar{z}_M(h)$. They can achieve $h' > h_M$ in
²⁵⁰ the next period if they invest $e = e_L$ today. In this case, there is no need to exert
²⁵¹ high effort e_H in human capital investment. The fast learners choose among three
²⁵² options: ($n = 1, e = 0$), ($n = 1, e = e_L$), and ($n = 0, e = e_L$).⁸

²⁵³ The decision rule for fast learners are as follows:

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

²⁵⁴ where

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

²⁵⁵

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

²⁵⁶ We set up our model so that $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.⁹

²⁵⁷ **Decision rule diagram:** Figure 1 illustrates the decision rule (n, e) as a function
²⁵⁸ of states (z, h, a) for households with $h_M \leq h < h_M \frac{1}{1-\delta}$. The human capital h
²⁵⁹ changes along the horizontal line and the idiosyncratic productivity z changes along
²⁶⁰ the vertical line. The two diagonal lines, $\bar{z}_M(h)$ and $\underline{z}_M(h)$ defined in (16), separate
²⁶¹ the state space into three areas: the unshaded area represents the non-learners,
²⁶² the lightly-shaded area represents the slow learners, and the darkly-shaded area
²⁶³ represents the fast learners. The areas are divided by four dashed horizontal lines
²⁶⁴ associated with cutoffs $\bar{z}_{non}^L(a)$, $\bar{z}_{slow}^L(a)$, $\underline{z}_{fast}^L(a)$, and $\bar{z}_{fast}^L(a)$ that are functions of
²⁶⁵ capital holding a and defined in (17), (18), (21), and (20).

²⁶⁶ This decision rule diagram is representative for households in other four ranges

⁷The choice between $(n = 0, e = e_H)$ and $(n = 0, e = 0)$ does not depend on z . For e_H to be relevant, λ must be large enough so that $(n = 0, e = e_H)$ is preferred to $(n = 0, e = 0)$. See the Appendix for details on the lower bound for λ .

⁸Similar 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 $(n = 0, e = 0)$.

⁹Appendix provides the parameter restrictions such that the condition for $(n = 0, e = e_H)$ to dominate $(n = 0, e = 0)$ is sufficient for $\bar{z}_{fast}^L(a) > \underline{z}_{fast}^L(a)$.

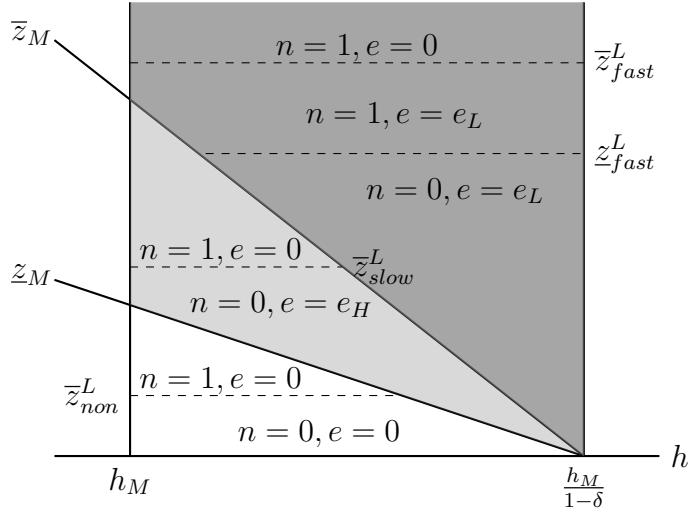


Figure 1: Decision Rule Diagram for $h_M \leq h < h_M(1 - \delta)^{-1}$

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 .

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

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

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

If $h_M \frac{1}{1-\delta} \leq h < h_H$, the four cutoffs for households are:¹⁰

$$\bar{z}_{non}^M(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'}{1+r'}]}{w} \quad (23)$$

$$\bar{z}_{slow}^M(a) := \frac{(\exp(\frac{\chi_n - \chi_e e_H}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}] + \lambda \frac{w'z'}{1+r'}}{w} \quad (24)$$

$$\underline{z}_{fast}^M(a) := \frac{(\exp(\frac{\chi_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}]}{w} \quad (25)$$

$$\bar{z}_{fast}^M(a) := \frac{\left\{ \lambda \left[\exp(\frac{\chi_e e_L}{1+\beta}) - 1 \right]^{-1} - 1 \right\} \frac{w'z'}{1+r'} - (1+r)a}{w} \quad (26)$$

If $h_H \leq h < h_H \frac{1}{1-\delta}$, the cutoffs are $\bar{z}_{non}^M \frac{1}{1+\lambda}$, $\bar{z}_{slow}^M \frac{1}{1+\lambda}$, $\underline{z}_{fast}^M \frac{1}{1+\lambda}$, and $\bar{z}_{fast}^M \frac{1}{1+\lambda}$.

All households with $h \geq h_H \frac{1}{1-\delta}$ are non-learners because their current human

¹⁰ Appendix provides parameter restrictions for $\bar{z}_{fast}^M(a) > \underline{z}_{fast}^M(a)$.

275 capital is enough for employment in the high sector next period even without any
 276 human capital investment. The only relevant cutoff for them is $\bar{z}_{non}^H(a) \frac{1}{1+\lambda}$ where

$$\bar{z}_{non}^H(a) := \frac{(\exp(\frac{x_n}{1+\beta}) - 1)[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'}]}{w} \quad (27)$$

277 3.2 The Effects of Uninsured Idiosyncratic Risk

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

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

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

290 From the perspective of human capital investment, the uncertain z' is associated
 291 with risk in the return to human capital. Conditional on working, households'
 292 income increases with z' : $c' = (1+r')a' + w'x(h')z'$. $\ln(c')$ is increasing and concave
 293 in z' , and a higher $x(h')$ increases the concavity.¹¹ Consider two levels of h' , $\bar{h}' > \underline{h}'$,
 294 a mean-preserving spread of z' distribution reduces the expected utility at both
 295 levels of h' but the reduction is larger for the higher level \bar{h}' . Hence, the expected
 296 utility gain of moving from \underline{h}' to \bar{h}' is smaller due to the idiosyncratic risk. Human
 297 capital investment is discouraged.

298 Taking into account endogenous labor supply reinforces the discouragement of
 299 human capital investment by the idiosyncratic risk. Recall from Section 3 that
 300 households with z' lower than a cutoff do not work. The endogenous labor supply
 301 therefore provides insurance against the lower tail risk of the idiosyncratic z' . More-
 302 over, the cutoff in z' is lower for those with higher human capital h' . This makes
 303 households with higher h' more exposed to the lower tail risk than those with lower

¹¹The marginal effect of z' on $\ln(c')$ is

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

The second derivative is

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

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

³⁰⁴ h' , further reducing the gain of human capital investment.

³⁰⁵ **Proposition 1** *The uninsured idiosyncratic risk in z' makes households in period
³⁰⁶ 1 save more, work more and invest less in human capital.*

³⁰⁷ 3.3 Period-1 Saving and Human Capital Investment

³⁰⁸ In this section, we study the impact of endogenous human capital investment on
³⁰⁹ households' saving decisions. Specifically, we compare optimal saving behavior in
³¹⁰ two scenarios: one in which households can choose to invest in human capital, and
³¹¹ an alternative scenario in which human capital is exogenously fixed.

³¹² When the optimal choice of human capital investment is zero, there will be no
³¹³ difference in optimal saving between the two scenarios. When the optimal choice of
³¹⁴ human capital investment is either e_L or e_H , we compare household's optimal saving
³¹⁵ with its counterpart when e is fixed to zero, i.e., $(n = 1, e = 0)$.¹²

³¹⁶ To make the human capital relevant, we assume that $n' = 1$ in period 2. The
³¹⁷ additive separability of work and human capital investment effort from consumption
³¹⁸ allows us to consider the optimal saving conditional on a given choice of labor supply
³¹⁹ and human capital investment.

³²⁰ In particular, the household maximizes expected lifetime utility:

$$\max_{a'} : \ln(c) + \beta \mathbb{E}_{z'}[\ln(c')], \quad (28)$$

³²¹ subject to the intertemporal budget constraint

$$c + a' = (1 + r)a + n(wzx(h)), \quad (29)$$

$$c' = (1 + r')a' + w'z'x(h'), \quad (30)$$

$$\text{with } h' = ze + (1 - \delta)h, e \in \{0, e_L, (1 - n)e_H\} \quad (31)$$

³²² 3.3.1 Effect of on-job-training on saving

³²³ We now compare the optimal saving between $(n = 1, e = e_L)$ and $(n = 1, e = 0)$,
³²⁴ where e_L allows households to move to a higher sector in period 2 with higher
³²⁵ sectoral productivity $x(h')$. We normalize $(1 + r') = 1$, $w' = 1$, and the period-2
³²⁶ productivity shock z' to $\ln z' \sim \mathcal{N}(0, \sigma_z^2)$ for analytical tractability.¹³ The effect of
³²⁷ human capital investment on period-2 income becomes:

$$c' = a' + txz', \quad (32)$$

¹²What about $(n = 0, e = 0)$? Its comparison with $(n = 0, e = e_H \text{ or } e_L)$ is meaningless since no labor income in either period and human capital is irrelevant. What if we compare $(n = 0, e = 0)$ to $(n = 1, e = e_L)$? Will these choices ever share a common state space? In other words, for the state space where $(n = 1, e = e_L)$, if we exogenously fix $e = 0$, will the households ever choose not to work, i.e., $n = 0$? [TO BE CHECKED]

¹³The normalization of z' is without loss of generality since the period-2 income is scaled by t that captures the effect of the mean of z' .

³²⁸ where we also normalize z' to $\ln z' \sim \mathcal{N}(0, \sigma_z^2)$, implying

$$\mathbb{E}[z'] = e^{\sigma_z^2/2}, \quad \text{Var}(z') = e^{\sigma_z^2}(e^{\sigma_z^2} - 1). \quad (33)$$

³²⁹ **Proposition 2** For $x = x_L < x^*$, $e = e_L$ lowers saving; for $x = x_H > x^*$, $e = e_L$
³³⁰ raises saving.

³³¹ **3.3.2 Effect of full-time training on saving**

³³² We next compare the optimal saving between $(n = 0, e = e_L \text{ or } e_H)$ and $(n = 1, e = 0)$.

³³⁴ **4 The Effects of an Anticipated Period-2 AI Shock**

³³⁵ Suppose that an AI shock is anticipated to occur in period 2 and to increase the
³³⁶ labor productivity for the low sector and the high sector but not the middle sector.

³³⁷ The effect of AI shock on the sectoral productivity is captured by γ with $0 < \gamma < 1$:

$$x(h') = \begin{cases} 1 - \lambda + \gamma\lambda & \text{low sector if } h' < h_M \\ 1 & \text{middle sector if } h_M < h' < h_H \\ 1 + \lambda + \gamma\lambda & \text{high sector if } h' > h_H \end{cases} \quad (34)$$

³³⁸ 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.

³⁴¹ **The non-learners:** The AI shock increases the labor income of households who
³⁴² work in the low sector or the high sector in period 2, i.e., those with $h < h_M \frac{1}{1-\delta}$ or
³⁴³ $h > h_H \frac{1}{1-\delta}$. The positive income effect makes them work less in period 1 so that
³⁴⁴ $\bar{z}_{non}^L(a)$ and $\bar{z}_{non}^H(a)$ increases in γ :

$$\bar{z}_{non}^i(a; \gamma) = \bar{z}_{non}^i(a; \gamma = 0) + \gamma\lambda \frac{w'z'}{w(1+r')} \left[\exp\left(\frac{\chi_n}{1+\beta}\right) - 1 \right] \text{ for } i = L, H$$

³⁴⁵ **The slow learners:** The AI shock reduces the incentive to work in the middle
³⁴⁶ sector in period 2, i.e., $\bar{z}_{slow}^L(a)$ is decreasing and $\bar{z}_{slow}^M(a)$ is increasing in γ :

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

³⁴⁷ Therefore, those with $h < h_M \frac{1}{1-\delta}$ invest less human capital and work more in period
³⁴⁸ 1 and those with $h > h_M \frac{1}{1-\delta}$ invest more human capital and work less.

349 **The fast learners:** Similar to the slow learners, the AI shock reduces households'
 350 incentive to work in the middle sector in period 2. As a result, human capital
 351 investment is lower for those with $h < h_M \frac{1}{1-\delta}$, and is higher for those with $h >$
 352 $h_M \frac{1}{1-\delta}$. The effects of AI shock γ on the cutoff governing human capital investment
 353 are:

$$\bar{z}_{fast}^L(a; \gamma) = \bar{z}_{fast}^L(a; \gamma = 0) - \gamma \lambda \frac{w' z'}{w(1+r')} \frac{\exp(\frac{\chi_e e_L}{1+\beta})}{\exp(\frac{\chi_e e_L}{1+\beta}) - 1}$$

$$\bar{z}_{fast}^M(a; \gamma) = \bar{z}_{fast}^M(a; \gamma = 0) + \gamma \lambda \frac{w' z'}{w(1+r')} \frac{1}{\exp(\frac{\chi_e e_L}{1+\beta}) - 1}$$

354 Conditional on the human capital investment being e_L , the fast learners' labor supply
 355 decision is affected by the AI shock via the future earning increase if the households
 356 will work in the high sector in period 2. That is, those with $h > h_M \frac{1}{1-\delta}$ work less
 357 in period 1, i.e., \underline{z}_{fast}^L increases in γ :

$$\underline{z}_{fast}^M(a; \gamma) = \underline{z}_{fast}^M(a; \gamma = 0) + \gamma \lambda \frac{w' z'}{w(1+r')} \left[\exp(\frac{\chi_n}{1+\beta}) - 1 \right]$$

358 4.1 Comparative Statics

359 The decision rules derived in the previous section imply that the fast learners invest
 360 in human capital if $z < \bar{z}_{fast}(h, a)$ and the slow learner invest in human capital if
 361 $z < \bar{z}_{slow}(h, a)$. The close form expressions of the cutoffs allow us to compare hu-
 362 man capital investment between groups of households with different levels of human
 363 capital and physical capital.

364 Effect of human capital h on human capital investment:

365 **Lemma 1** Both the fast learners and the slow learners with $h < \frac{h_M}{1-\delta}$ invest more in
 366 human capital than their counterparts with $h > \frac{h_M}{1-\delta}$:

$$\frac{\bar{z}_{fast}^L}{1-\lambda} > \bar{z}_{fast}^M ; \bar{z}_{fast}^L > \frac{\bar{z}_{fast}^M}{1+\lambda}$$

$$\frac{\bar{z}_{slow}^L}{1-\lambda} > \bar{z}_{slow}^M ; \bar{z}_{slow}^L > \frac{\bar{z}_{slow}^M}{1+\lambda}$$

367 Figure 2 provides an illustration to this proposition. The striped areas indicate
 368 the state space for positive human capital investment. The darkly-shaded areas
 369 correspond to the fast learners. The lightly-shaded areas correspond to the slow
 370 learners. Let us take the slow learners as an example. Those with $h < \frac{h_M}{1-\delta}$ need to
 371 invest e_H to either stay in or to move up to the middle sector next period. Those
 372 with $h > \frac{h_M}{1-\delta}$ need to invest e_H to either stay in or to move up to the high sector.
 373 The most productive households does not invest in human capital because it requires

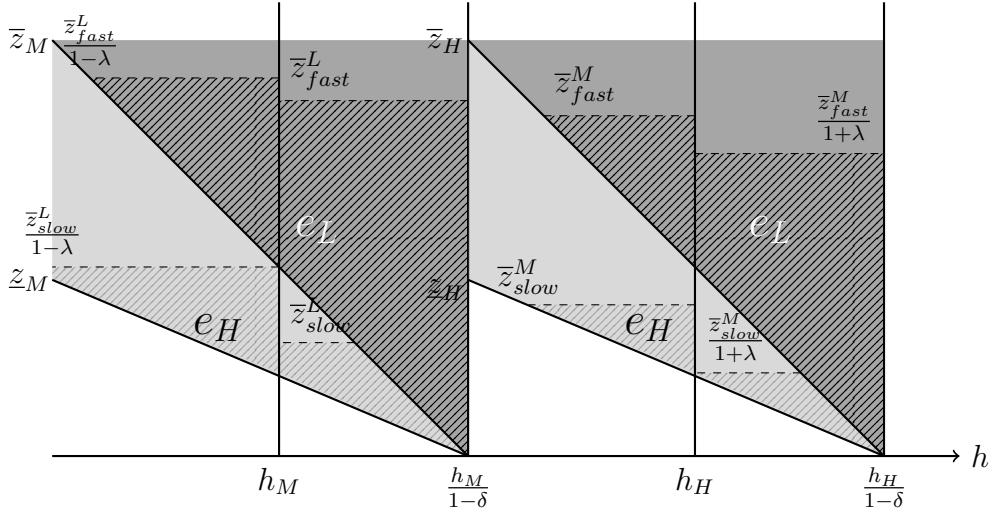


Figure 2: State Space for Human Capital Investment

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

³⁷⁴ giving up their labor earning. This productivity cutoff is lower for those with higher
³⁷⁵ human capital, meaning that their investment in human capital is lower than those
³⁷⁶ with lower human capital.

³⁷⁷ Effect of physical capital a on human capital investment:

³⁷⁸ **Lemma 2** *The fast learners with lower asset holding invest more in human capital:*

$$\frac{\partial \bar{z}_{fast}^L(a)}{\partial a} < 0 ; \frac{\partial \bar{z}_{fast}^M(a)}{\partial a} < 0$$

³⁷⁹ *The slow learners with lower asset holding invest more in human capital if and only*
³⁸⁰ *if $\chi_n < \chi_e e_H$:*

$$\frac{\partial \bar{z}_{slow}^L(a)}{\partial a} < 0 \text{ and } \frac{\partial \bar{z}_{slow}^M(a)}{\partial a} < 0 \text{ iff } \chi_n < \chi_e e_H$$

³⁸¹ 4.1.1 AI effect on human capital inequality

³⁸² Recall from Lemma 1 that, without the AI shock, households with low h invest
³⁸³ more in human capital than households with high h . The analysis above shows
³⁸⁴ that the AI shock discourages human capital investment for those with low h but
³⁸⁵ encourages it for those with high h . Therefore, a small AI shock reduces human
³⁸⁶ capital investment disparity between groups with different levels of h , and a large
³⁸⁷ AI shock could lead to a reversal in the comparison, making households with high
³⁸⁸ h invest more in human capital than households with low h . The human capital
³⁸⁹ distribution will be more unequal due to the AI shock.

³⁹⁰ **Proposition 3** *AI shock increases human capital inequality.*

Table I: Parameters for the Calibration

Parameter	Value	Description	Target or Reference
β	0.91795	Time discount factor	Annual interest rate
ρ_z	0.94	Persistence of z shocks	See text
σ_z	0.287	Standard deviation of z shocks	Earnings Gini
\underline{a}	0	Borrowing limit	See text
χ_n	2.47	Disutility from working	Employment rate
χ_e	1.48	Disutility from HC effort	See text
\bar{n}	1/3	Hours worked	Average hours worked
e_H	1/3	High level of effort	Average hours worked
e_L	1/6	Low level of effort	See text
h_M	0.41	Human capital cutoff for M	See text
h_H	0.96	Human capital cutoff for H	See text
λ	0.2	Skill premium	Income Gini
α	0.36	Capital income share	Standard value
δ	0.1	Capital depreciation rate	Standard value

391 **Limitations to the two-period model:** In the two-period model, we take the
 392 period-1 asset holding as exogenous. In the full model, the idiosyncratic risk in-
 393 creases households saving and leads to more asset holding. According to Lemma
 394 2, more asset holding reduces human capital investment for the fast learners and
 395 reduces human capital investment for the slow learners if and only if $\chi_n < \chi_e e_H$.

396 5 A Quantitative Model

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

400 5.1 Calibration

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

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

409 We calibrate parameters regarding labor productivity process as follows. We
 410 assume that x follows the AR(1) process in logs: $\log z' = \rho_z \log z + \epsilon_z$, where
 411 $\epsilon_z \sim N(0, \sigma_z^2)$. The shock process is discretized using the Tauchen (1986) method,

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

412 resulting in a transition probability matrix with 9 grids. The persistence parameter
413 $\rho_z = 0.94$ is chosen based on estimates from the literature. The standard deviation
414 σ_z , is chosen to match the earnings Gini coefficient of 0.63.

415 We deviate from the two-period model by assuming that the labor supply is a
416 discrete choice between 0 and $\bar{n} = 1/3$. This change only rescales the two-period
417 model without altering the trade-off facing the households. But such rescaling facil-
418 itates the interpretation that households are deciding whether to allocate one-third
419 of their fixed time endowment to work. The high-level human capital accumulation
420 effort, e_H is assumed to equal \bar{n} . The low-level effort, e_L is set to half of e_H . The skill
421 premium across sectors, λ , is set at 0.2 to match the income Gini coefficient. Human
422 capital cutoffs, h_M and h_H , are set so that the population shares in low, middle, and
423 high sectors are, respectively, 20, 40, and 40 percent. This population distribution
424 roughly matches the fractions of U.S. workers in 2014 who are employed in routine
425 manual occupations (low sector), routine cognitive and non-routine manual (middle
426 sector), and non-routine cognitive (high sector) (Cortes *et al.*, 2017).

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

429 5.2 Key Moments: Data vs. Model

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

⁴⁴⁴ data: the empirical wealth Gini is 0.78, while the model produces a value of 0.76.
⁴⁴⁵ This highlights the model's ability to capture substantial wealth inequality in the
⁴⁴⁶ economy.

⁴⁴⁷ 5.3 Steady-state Distribution

⁴⁴⁸ Table III presents the steady-state distribution of population, employment, and
⁴⁴⁹ assets across sectors. The population shares are calibrated to 20%, 40%, and
⁴⁵⁰ 40% by adjusting the human capital thresholds that define sectors. The shares
⁴⁵¹ of employment and assets are endogenously determined by households' labor supply
⁴⁵² and savings decisions. Notably, the high sector accounts for 46% of total employ-
⁴⁵³ ment—exceeding its population share—indicating that a disproportionate number
⁴⁵⁴ of households choose to work in that sector. Asset holdings are even more skewed:
⁴⁵⁵ 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.

⁴⁵⁶ 6 AI's Impact on Human Capital Adjustments

⁴⁵⁷ We now introduce AI technology into the quantitative model, assuming that it will
⁴⁵⁸ be implemented in 10 years and that households have full information about its
⁴⁵⁹ arrival. We examine both the transition dynamics and the differences between the
⁴⁶⁰ initial and new steady states. This framework allows us to analyze how the economy
⁴⁶¹ adjusts in anticipation of, and in response to, the adoption of AI.

⁴⁶² The effect of AI on the sectorial productivity is modeled as in (34) with $\gamma = 0.3$.
⁴⁶³ That is, AI boosted the productivity of the low sector workers by 7.5% and the
⁴⁶⁴ productivity of the high sector workers by 5%, leaving the middle sector intact.
⁴⁶⁵ It captures the key idea that AI increases average labor productivity (Acemoglu
⁴⁶⁶ and Restrepo, 2019), but reduces the earning premium for the middle sector, and
⁴⁶⁷ enlarges the earning premium for the higher sector relative the middle sector.

⁴⁶⁸ 6.1 Human Capital Adjustments

⁴⁶⁹ Given the employment distribution in the initial steady state, AI is projected to
⁴⁷⁰ increase the economy's labor productivity by 4% on average, assuming households

Figure 3: Steady-state Human Capital Distribution

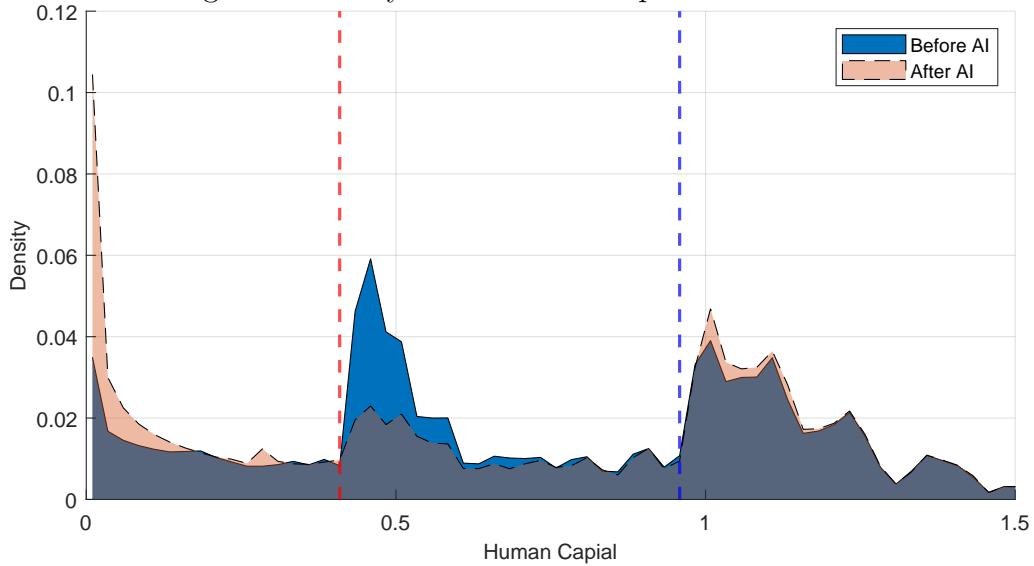


Figure 4: Steady-state Human Capital Investment

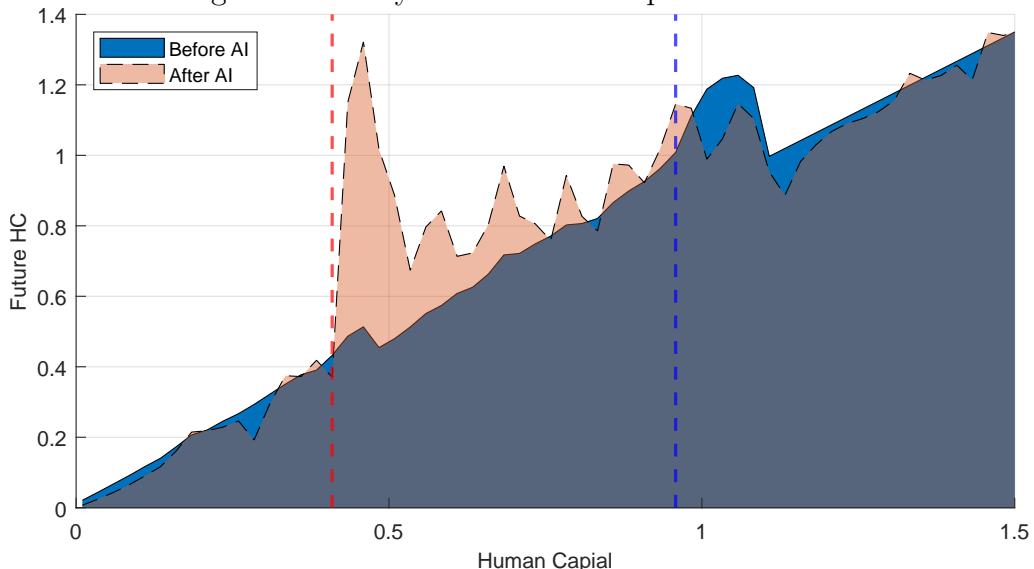
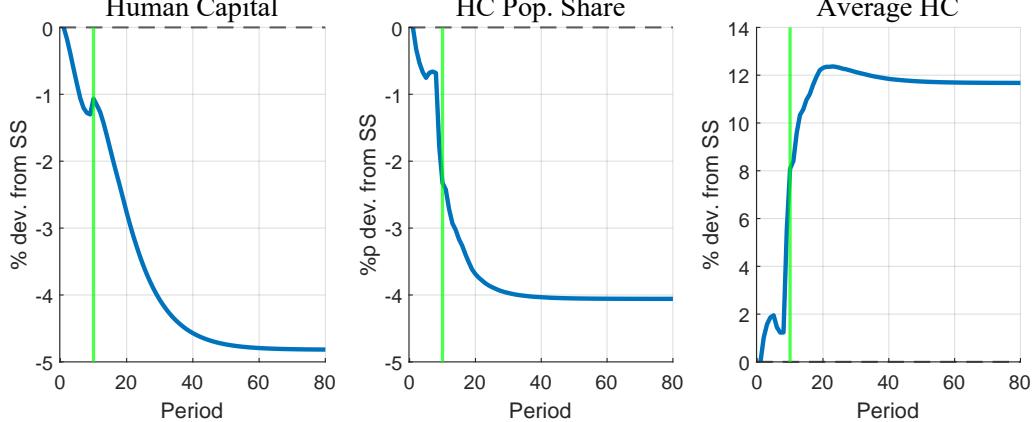


Figure 5: Transition Path for Human Capital Investment



⁴⁷¹ do not alter their decisions in response. However, changes in earning premiums
⁴⁷² incentivize households to adjust their human capital investments.

⁴⁷³ **Steady-state human capital distribution:** Figure 3 illustrates how households
⁴⁷⁴ reallocate across sectors in the new steady state relative to the initial one. The x-axis
⁴⁷⁵ denotes the level of human capital, while the y-axis indicates the mass of households
⁴⁷⁶ at each human capital level. The red vertical line marks the cutoff between the low
⁴⁷⁷ and middle sectors, and the blue vertical line marks the cutoff between the middle
⁴⁷⁸ and high sectors.

⁴⁷⁹ The gray shaded area shows the overlap between the two steady-state distri-
⁴⁸⁰ butions. Within each sector, the distribution of households is skewed to the left,
⁴⁸¹ reflecting the tendency for human capital investment to be concentrated among
⁴⁸² those near the sectoral cutoffs. As shown in the decision rule diagram in Figure 2,
⁴⁸³ some households seek to upgrade their skills, while others aim to remain in more
⁴⁸⁴ skilled sectors. The blue shaded area highlights the mass of households who have
⁴⁸⁵ exited the middle sector following the AI shock. The pink areas represent the addi-
⁴⁸⁶ tional mass of households in the new steady-state distribution, concentrated at the
⁴⁸⁷ lower end of the low sector and the lower end of the high sector.

⁴⁸⁸ **Steady-state human capital investment:** This reallocation pattern reflects
⁴⁸⁹ shifts in human capital investment incentives driven by AI's impact on the skill
⁴⁹⁰ premium. Figure 4 plots human capital investment decisions in the initial and new
⁴⁹¹ steady states across different human capital levels. Because both the productivity
⁴⁹² shock (z) and current asset holdings (a) influence human capital investment, the
⁴⁹³ y-axis shows the weighted average of next-period human capital, where the weights
⁴⁹⁴ reflect the steady-state distribution of households by productivity shock and wealth
⁴⁹⁵ at each human capital level.

⁴⁹⁶ The changes in decision rules before and after the AI shock are highlighted in
⁴⁹⁷ the blue shaded area, where next-period human capital in the new steady state
⁴⁹⁸ is lower than in the initial steady state, and in the pick shaded area, where it is
⁴⁹⁹ higher. The most notable change is that the middle-sector households substantially
⁵⁰⁰ intensify their human capital investment, aiming to transition into high-sector roles.
⁵⁰¹ In contrast, households in the low sector reduce their human capital investment,
⁵⁰² causing those who might have moved up to the middle sector to remain in the low
⁵⁰³ sector or even drift further down to the very bottom of human capital distribution
⁵⁰⁴ as shown in Figure 3.

⁵⁰⁵ Somewhat surprisingly, most high-sector workers in the new steady state decrease
⁵⁰⁶ their human capital investment relative to the initial steady state. This is primarily
⁵⁰⁷ a composition effect: as more households move from the middle-sector to the high
⁵⁰⁸ sectors, the average asset holdings among high-sector households decline, making
⁵⁰⁹ intensive human capital investment less affordable [note that this is not supported

510 by the average asset in transition dynamics figure 9].

511 **Transition path** Figure 5 reports the transition dynamics of aggregate human
512 capital from the initial to the new steady state. The figure also displays its extensive
513 margin (the share of households making positive human capital investments) and
514 intensive margin (average human capital per household among those who invest).

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

519 Additionally, human capital accumulation becomes increasingly concentrated
520 among a smaller share of the population. The proportion of households making
521 positive human capital investments steadily declines, ultimately stabilizing at a level
522 4% lower than in the initial steady state. Meanwhile, the average human capital
523 among those who invest rises, reaching a level 12% higher than the initial steady
524 state in the long run.¹⁴

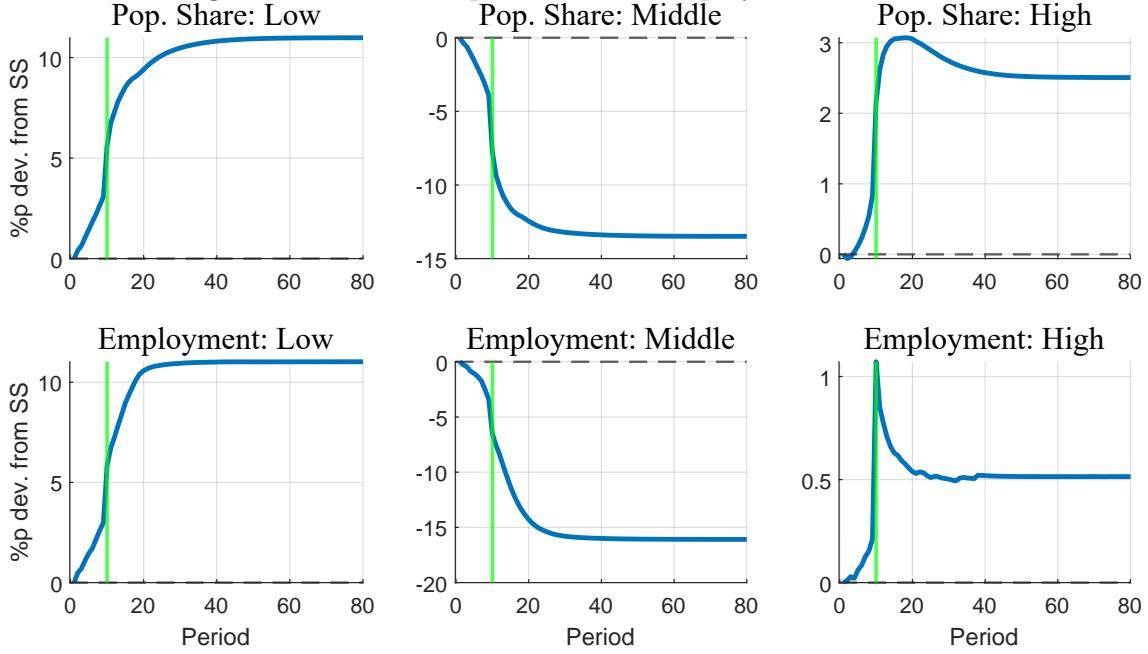
525 6.2 Job Polarization

526 An important implication of human capital adjustments to the AI shock is job
527 polarization. Figure 6 illustrate the transition paths of population shares and em-
528 ployment rates in each sector. Notably, the middle sector experiences a significant
529 decline, with its population share decreasing by approximately 13%. Additionally,
530 employment within this sector plummets to a level 16% lower than the initial steady
531 state. In contrast, both the low and high sectors see increases in their population
532 shares and employment rates. These dynamics indicate a reallocation of *workers*
533 from the middle sector to the low and high sectors following the introduction of AI.

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

¹⁴The only exception to those patterns occurs at period 10 when the positive effects of AI on sectoral productivity are realized.

Figure 6: 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.

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

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

560 7 The Aggregate and Distributional Effects of AI

561 The aggregate and distributional effects of AI are shaped by both its direct impact on
 562 sectoral productivity and the endogenous response of human capital accumulation.
 563 By altering sectoral productivity, AI changes labor earnings, which in turn influences

564 labor supply decisions and savings through income effects. Consequently, AI directly
565 affects the supply of labor and capital, generating aggregate economic responses.
566 Because AI's productivity effects are heterogeneous across sectors, its impact is
567 inherently distributional.

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

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

580 By contrasting the transition dynamics across these two economies, we can disen-
581 tangle the direct and indirect effects of AI. The transition path in the No-HC-model
582 isolates the direct impact of AI on aggregate and distributional outcomes, as it ab-
583 stracts from any human capital adjustments. The difference in outcomes between
584 the benchmark and the No-HC-model then reveals the indirect effects of AI that
585 operate through households' adjustments in human capital. This decomposition al-
586 lows us to assess the relative importance of human capital dynamics in driving both
587 the aggregate and distributional consequences of AI.

588 *7.1 Aggregate Implications*

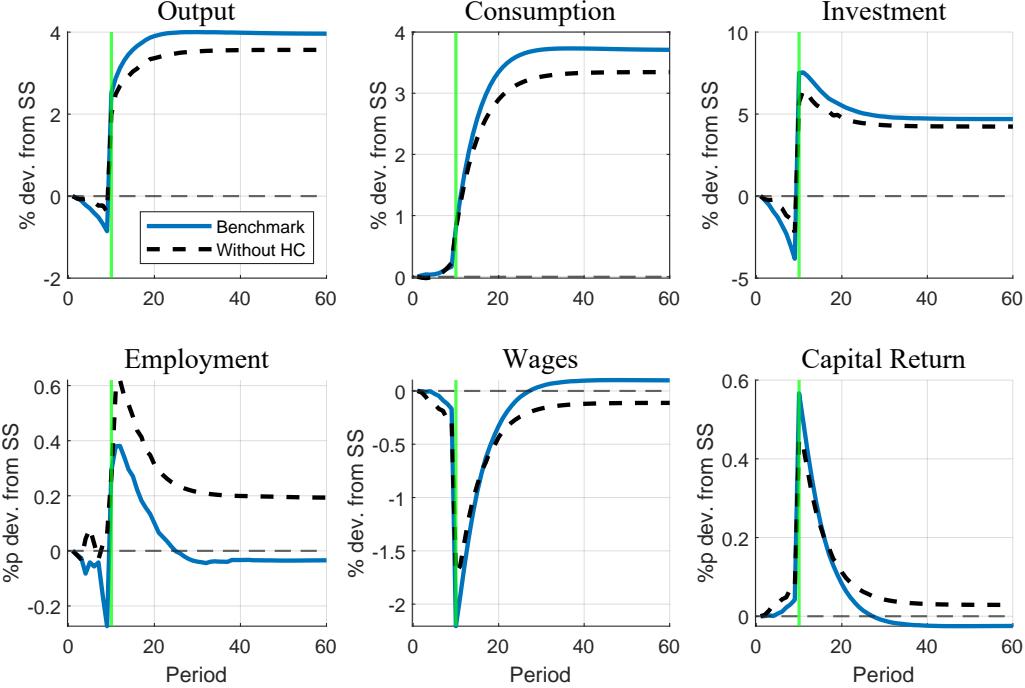
589 Figure 7 shows the transition paths of key macroeconomic variables—output, con-
590 sumption, investment, and employment—as well as factor prices, including the wage
591 rate and capital return. The blue solid lines depict results from the benchmark model
592 with endogenous human capital adjustment, while the black dashed lines represent
593 the No-HC model in which human capital is held fixed.

594 **7.1.1 AI's direct impacts**

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

599 Before the implementation of AI, sectoral productivity is unchanged; the only
600 difference is households' awareness of future increases in productivity in the low and
601 high sectors beginning in period 10. This anticipation raises households' expected

Figure 7: 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.

602 lifetime income, prompting them to save less and consume more ahead of the actual
 603 productivity gains. As a result, aggregate capital stock falls, which lowers output and
 604 reduces the marginal product of labor while raising the marginal product of capital.
 605 Employment remains largely unchanged in this period, as sectoral productivity has
 606 not yet shifted.

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

614 7.1.2 AI's indirect impacts via endogenous human capital adjustments

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

619 In anticipation of AI, employment declines as some households temporarily exit
 620 the labor market to invest in human capital and prepare for the post-AI economy.¹⁵

¹⁵Empirical studies, such as Lerch (2021) and Faber *et al.*, (2022), support the short-term adverse

621 During this period, labor productivity remains unchanged, so the decline in em-
622 ployment directly translates to a reduction in output. Consistent with standard
623 consumption-smoothing behavior, this reduction is mainly absorbed by lower in-
624 vestment. Meanwhile, the drop in employment mitigates the direct effects of AI on
625 both wages and capital returns prior to the AI implementation.

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

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

637 *7.2 Distributional Implications*

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

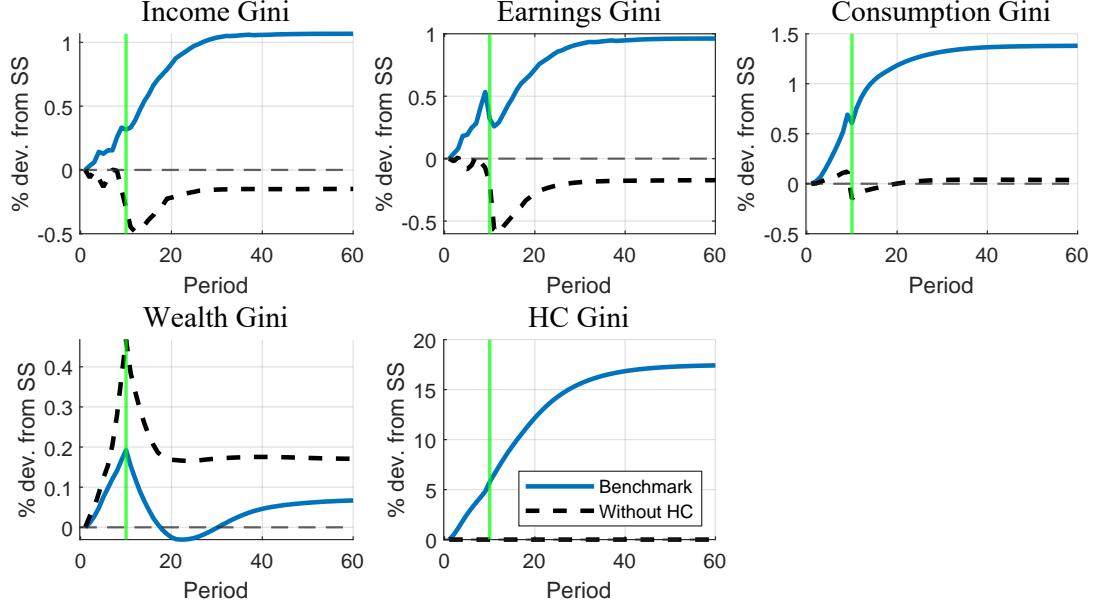
642 Figure 8 shows the transition paths of Gini coefficients for earnings (labor in-
643 come), total income (capital and labor income), consumption, wealth (asset hold-
644 ings), and human capital. The black dashed lines represent results from the No-HC
645 model, capturing the direct impact of AI without human capital adjustment. In
646 contrast, the blue solid lines reflect the benchmark model, where human capital re-
647 sponds endogenously to both anticipated and realized changes in the skill premium
648 induced by AI.

649 *7.2.1 Income, earnings, and consumption inequalities*

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

653 **AI's direct impacts:** Without any human capital adjustments, AI's impact on
654 inequalities is primarily driven by productivity gains in the low and high sectors
655 – 7.5% and 5%, respectively. As a result, there is little direct impact on income
effects of AI adoption on labor markets.

Figure 8: 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.

and earnings Gini coefficients in anticipation of AI before period 10. After AI is implemented, both income and earnings inequality decline: higher labor productivity raises earnings in the low sector, while wage declines in the middle sector compress the distribution. Consumption inequality remains largely unchanged throughout the transition.

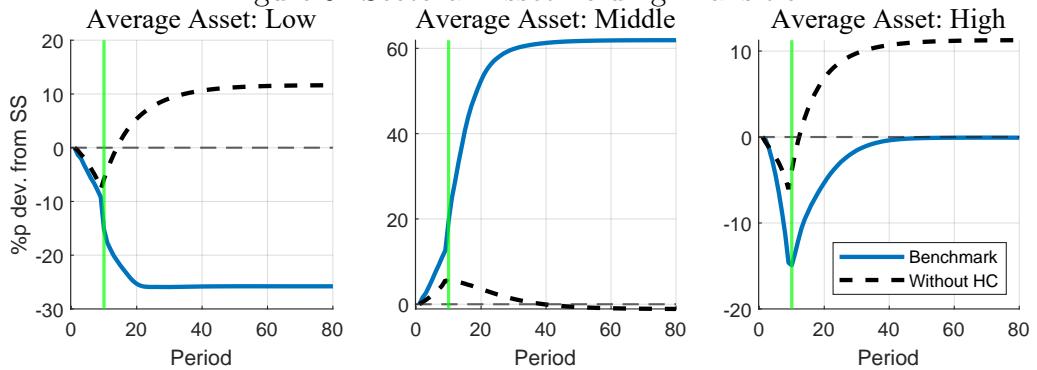
Effects of AI-induced human capital adjustments: Allowing human capital to adjust endogenously, however, leads to pronounced job polarization, as shown in Section 6.2. Households who would have qualified for middle-sector jobs now transition to either the low or high sector. Those moving to the low sector see reduced labor earnings, while those shifting to the high sector enjoy increased earnings. This polarization drives up earnings and income inequality, both before and after AI is implemented. As income disparities widen, consumption inequality also increases.

7.2.2 Wealth inequality

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

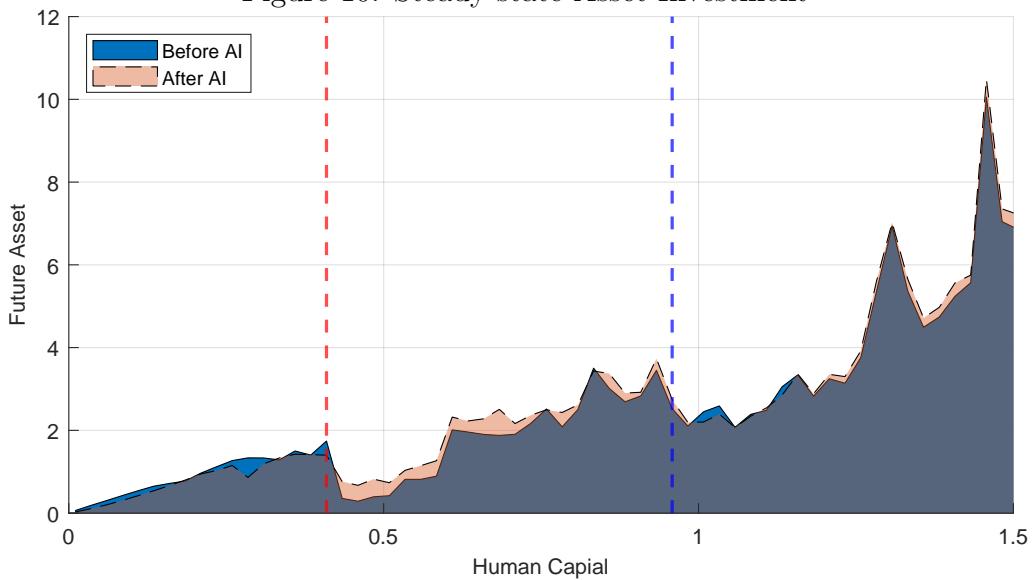
To disentangle the direct and indirect effects of AI on wealth inequality, Figure 9 presents the sectoral transition paths for asset holdings, while Figure 10 compares steady-state asset investment decisions across different human capital levels.

Figure 9: Sectoral Asset-holding Transition



Note: The transition paths of average capital within each sector. 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. "Average Capital" denotes the physical assets per household in each sector.

Figure 10: Steady-state Asset Investment



677 [Add a figure that compares the steady-state asset investment in the No-HC-
678 model (a counterpart of Figure 10).]

679 **AI's direct impacts:** We first focus on the black dashed lines in Figure 9. With-
680 out households reallocation across sectors, total assets and average asset holdings
681 follow similar patterns. In both the low and high sectors, households reduce their
682 savings in anticipation of AI, expecting higher lifetime labor income. After AI is
683 implemented at period 10, their savings increase alongside rising labor incomes.
684 In contrast, households in the middle sector, anticipating a negative income effect
685 from AI due to a lower wage rate, increase their savings prior to period 10. Once
686 AI is introduced and the wage rate recovers, middle-sector households reduce their
687 savings.

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

693 **Effects of AI-induced human capital adjustments:** Average asset holding
694 isolates us from movements in the population share along the transition path.

695 1. Selection effect is dominant: From middle to low: low productivity and
696 middle-sector level wealth. Due to higher wealth level than the low-sector, the influx
697 should have increased the arrearage asset holding of the low sector, but because
698 they are low productivity households and they experience a reduction of sectoral
699 productivity. [But we still should have seen an increase in Average asset before
700 period 10???]

701 From middle to high: high productivity and middle-sector level wealth. Due
702 to lower wealth level than the high-sector, the influx of middle-sector households
703 reduces the average asset holding of the high sector. But since they are high-
704 productivity households, their saving rate increases.

705 2. Precautionary saving motive changes: For the low sector, the reduction of
706 skill premium in the benchmark model implies a reduction in idiosyncratic risk, so
707 households reduce saving. For the high sector, the opposite is true. In the No-HC-
708 model, changes in skill premium does not affect idiosyncratic risk since households
709 cannot change sector.

710 Allowing for endogenous human capital adjustment results in time-varying pop-
711 ulation shares across sectors along the transition path, which drives the divergence
712 between sectoral total and average asset holdings. In both the low and high sectors,
713 although the average household's asset holding declines substantially, the total as-
714 set holding in the low sector remains relatively stable, and in the high sector even
715 increases, due to the influx of households from the middle sector. Conversely, while

716 the average household in the middle sector saves more, the total asset holding in
717 the middle sector declines as its population share shrinks. These offsetting effects
718 between sectoral average asset holdings and shifting population shares help dampen
719 fluctuations in the wealth Gini coefficient along the transition path, compared to
720 the No-HC model (see Figure 8).

721 I cannot explain why the wealth gini in the benchmark model is lower than in
722 the No-HC-model, since from the total asset graphs, benchmark model has more
723 total assets in the higher sector in new steady state. So we have to turn to the
724 comparison of asset holding decision rule.

725 **Steady-state change in asset investment:** To explain the contrasting sectoral
726 changes in average asset holdings between the benchmark model and the No-HC-
727 model in the new steady state, Figure 10 shows how next-period asset holdings
728 change from the initial to the new steady state at each human capital level in the
729 benchmark model, while Figure XXX presents the corresponding results for the No-
730 HC-model. As in Figure 4, the y-axis displays the weighted average of next-period
731 asset holdings, with weights reflecting the steady-state distribution of households
732 by productivity shocks (z) and wealth (a) at each human capital level. Pink shaded
733 areas indicate an increase in next-period asset holdings, while blue shaded areas
734 indicate a decrease.

735 Note that in the benchmark model, the pink shaded areas are mostly located
736 in the middle sector. This is due to a “selection effect” since the households who
737 stays in the middle sector in the new steady after the AI shock are those with
738 higher productivity than those in the initial steady state. It is because those with
739 lower productivity would have already flow in the low sector. As productivity is
740 positively correlated with wealth, households remaining in the middle sector in the
741 new steady state tends to have more wealth, which boosts their saving. I cannot
742 explain why the high-sector average asset-holding remains unchanged in the new
743 steady state whereas the asset investment figure shows that the next-period asset
744 holding is reduced in the high sector.

745 Reduction in saving in the low sector, because of the influx of low-productivity
746 households from the middle sector? High sector, it is a mix so that average asset
747 holding remains the same as the initial steady state. in the benchmark, in the initial
748 steady state, the middle sector’s idiosyncratic productivity on average is lower than
749 the high sector households (that is the why they stay in the middle sector that has
750 requires lower human capital investment. Therefore, those moving to the high sector
751 has on average lower z and lower a . That explains why there is a reduction of asset
752 investment in the low end to high sector in the new steady state as the result of
753 more mover from the middle sector. Income effects are still present for the higher
754 end of high sector, which acts as a counterforce to the reduction of average asset
755 holding in the low end.

756 **8 Conclusion**

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

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

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823 A Parameter Restrictions for the Two-Period Model

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

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

826 or equivalently:

$$\lambda \geq \underline{\lambda}_1 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}} \left(1 - \frac{1}{\exp(\frac{\chi_e e_H}{1+\beta})} \right) \text{ if } h < h_M \frac{1}{1-\delta} \quad (35)$$

$$\lambda \geq \underline{\lambda}_3 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}} \left(\exp(\frac{\chi_e e_H}{1+\beta}) - 1 \right) \text{ if } h \geq h_M \frac{1}{1-\delta} \quad (36)$$

827 To avoid $(n = 1, e = e_L)$ from being a dominated choice, we need another lower
828 bound for λ . To see it, recall that $(n = 1, e = 0)$ is better than $(n = 1, e = e_L)$
829 if $z > \bar{z}_{fast}$, and $(n = 1, e = e_L)$ is better than $(n = 0, e = e_L)$ if $z > \underline{z}_{fast}$.
830 $(n = 1, e = e_L)$ is therefore the best choice over the interval $(\underline{z}_{fast}, \bar{z}_{fast})$. For such
831 an interval to exist, it must be the case that when $z = \underline{z}_{fast}$, $z < \bar{z}_{fast}$.

832 $z = \underline{z}_{fast}$ means that the fast learners are indifferent between $(n = 1, e = e_L)$
833 and $(n = 0, e = e_L)$ so that

$$(1+r)a + wzx(h) + \frac{w'z'}{1+r'} = \exp(\frac{\chi_n}{1+\beta}) \left[(1+r)a + \frac{w'z'}{1+r'} \right] \text{ if } h < h_M \frac{1}{1-\delta} \quad (37)$$

$$(1+r)a + wzx(h) + \frac{w'z'(1+\lambda)}{1+r'} = \exp(\frac{\chi_n}{1+\beta}) \left[(1+r)a + \frac{w'z'(1+\lambda)}{1+r'} \right] \text{ if } h \geq h_M \frac{1}{1-\delta} \quad (38)$$

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

$$(1+\beta) \ln \frac{c(n=1, e=e_L)}{c(n=1, e=0)} \geq \chi_e e_L \quad (39)$$

835 If $h < h_M \frac{1}{1-\delta}$, this inequality is:

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

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

$$\lambda \geq \underline{\lambda}_2 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}} \left(1 - \frac{1}{\exp(\frac{\chi_e e_L}{1+\beta})} \right) \exp(\frac{\chi_n}{1+\beta}) \quad (40)$$

837 If $h > h_M \frac{1}{1-\delta}$, inequality (39) is:

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

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

$$\lambda \geq \underline{\lambda}_4 := \frac{(1+r)a + \frac{w'z'}{1+r'}}{\frac{w'z'}{1+r'}} \frac{\left(\exp\left(\frac{\chi_e e_L}{1+\beta}\right) - 1\right) \exp\left(\frac{\chi_n}{1+\beta}\right)}{\exp\left(\frac{\chi_e e_L}{1+\beta}\right) + \exp\left(\frac{\chi_n}{1+\beta}\right) - \exp\left(\frac{\chi_e e_L + \chi_n}{1+\beta}\right)} \quad (41)$$

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

$$\exp\left(\frac{\chi_e e_H}{1+\beta}\right) > \frac{\exp\left(\frac{\chi_e e_L}{1+\beta}\right)}{\exp\left(\frac{\chi_e e_L}{1+\beta}\right) + \exp\left(\frac{\chi_n}{1+\beta}\right) - \exp\left(\frac{\chi_e e_L + \chi_n}{1+\beta}\right)} \quad (42)$$

840 Therefore, the inequality above implies that the conditions (35) and (36) are sufficient for the conditions (40) and (41). Furthermore, $\lambda_3 \geq \lambda_1$ so that the condition 842 (36) is sufficient for the condition (35).

843 We can then conclude that the conditions (36) and (42) are sufficient for 1)
844 the slower learners always prefers $(n = 0, e = e_H)$ over $(n = 0, e = 0)$, and 2)
845 $\bar{z}_{fast} > \underline{z}_{fast}$.

846 B Cutoffs ranking for the Two-Period Model

847 For the fast learners, their cutoffs rank as follows

$$\frac{\bar{z}_{fast}^L(a)}{1-\lambda} > \bar{z}_{fast}^L(a) > \bar{z}_{fast}^M(a) > \frac{\bar{z}_{fast}^M(a)}{1+\lambda} \quad (43)$$

$$\frac{\underline{z}_{fast}^L(a)}{1-\lambda} > \underline{z}_{fast}^M(a) > \underline{z}_{fast}^L(a) > \frac{\underline{z}_{fast}^M(a)}{1+\lambda} \quad (44)$$

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

$$\frac{\bar{z}_{slow}^L(a)}{1-\lambda} > \bar{z}_{slow}^M(a) > \bar{z}_{slow}^L(a) > \frac{\bar{z}_{slow}^M(a)}{1+\lambda} \quad (45)$$

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

$$\frac{\bar{z}_{non}^L(a)}{1-\lambda} > \bar{z}_{non}^M(a) > \frac{\bar{z}_{non}^H(a)}{1+\lambda} > \frac{\bar{z}_{non}^M(a)}{1+\lambda} \quad (46)$$

$$\bar{z}_{non}^M(a) > \bar{z}_{non}^L(a) \quad (47)$$

850 C Computational Procedure for the Quantitative Model

851 C.1 Steady-state Equilibrium

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

- 856 1. We choose the number of grid for the risk-free asset, a , human capital, h , and
 857 the idiosyncratic labor productivity, x . We set $N_a = 151$, $N_h = 151$, and
 858 $N_x = 9$ where N denotes the number of grid for each variable. To better
 859 incorporate the saving decisions of households near the borrowing constraint,
 860 we assign more points to the lower range of the asset and human capital.
- 861 2. Productivity x is equally distributed on the range $[-3\sigma_x/\sqrt{1-\rho_x^2}]$. As shown
 862 in the paper, we construct the transition probability matrix $\pi(x'|x)$ of the
 863 idiosyncratic labor productivity.
- 864 3. Given the values of parameters, we find the value functions for each state
 865 (a, h, x) . We also obtain the decision rules: savings $a'(a, h, x)$, and $h'(a, h, x)$.
 866 The computation steps are as follow:
- 867 4. After obtaining the value functions and the decision rules, we compute the
 868 time-invariant distribution $\mu(a, h, x)$.
- 869 5. If the variables of interest are close to the targeted values, we have found the
 870 steady-state. If not, we choose the new parameters and redo the above steps.

871 C.2 Transition Dynamics

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

- 874 1. We obtain the initial steady state and the new steady state.
- 875 2. We assume that the economy arrives at the new steady state at time T . We
 876 set the T to 100. The unit of time is a year.
- 877 3. We initialize the capital-labor ratio $\{K_t/L_t\}_{t=2}^{T-1}$ and obtain the associated
 878 factor prices $\{r_t, w_t\}_{t=2}^{T-1}$.
- 879 4. As we know the value functions at time T , we can obtain the value functions
 880 and the decision rules in the transition path from $t = T - 1$ to 1.
- 881 5. We compute the measures $\{\mu_t\}_{t=2}^T$ with the measures at the initial steady state
 882 and the decision rules in the transition path.
- 883 6. We obtain the aggregate variables in the transition path with the decision rules
 884 and the distribution measures.
- 885 7. We compare the assumed paths of capital and the effective labor with the
 886 updated ones. If the absolute difference between them in each period is close
 887 enough, we obtain the converged transition path. Otherwise, we assume new
 888 capital-labor ratio and go back to 3.

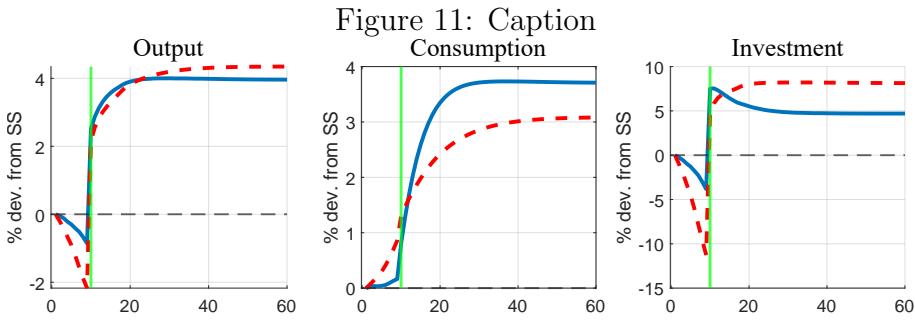


Figure 11: Caption
Consumption

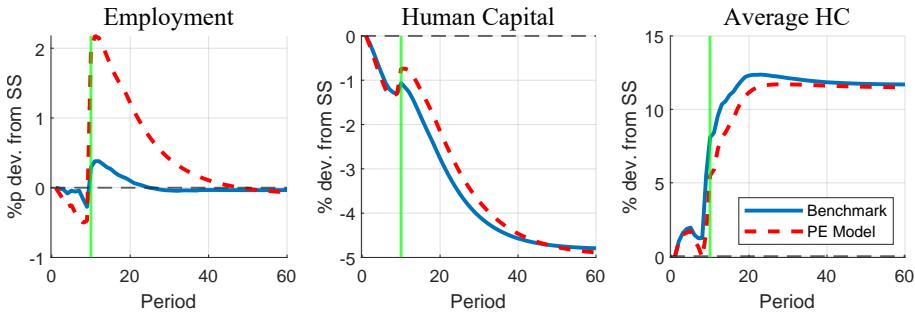


Figure 11: Caption

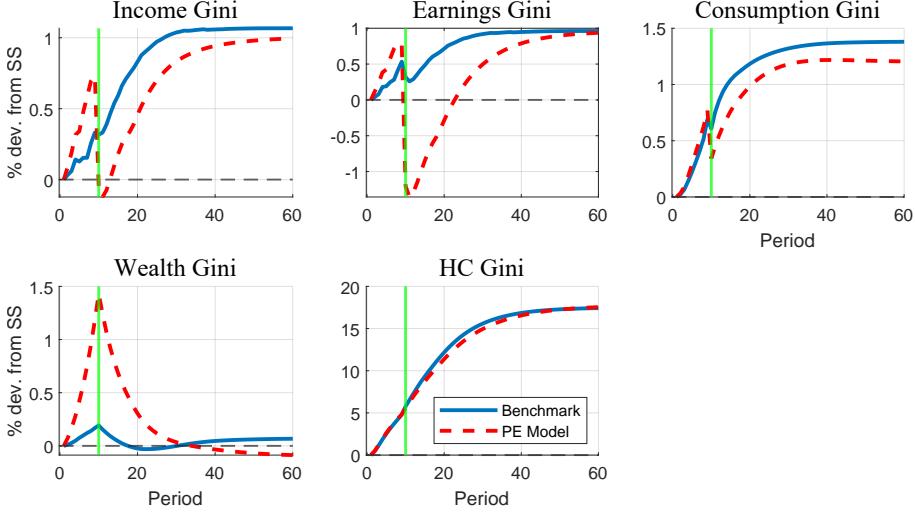


Figure 12: Caption

889 D Investigating the GE channel of AI's impact

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

896 Figure ?? compares the transition dynamics between scenarios with and without
897 human capital adjustments, while holding wages and capital returns fixed at their
898 initial steady-state levels to eliminate GE effects. We refer to the former as the
899 "PE Model" and the latter as the "No-HC PE Model." The difference between the
900 solid blue line and the dashed red line isolates the effect of redistribution channel.

901 Comparing this difference to the gap between the benchmark model and the No
902 HC model in Figure 7 enables us to evaluate the importance of the redistribution
903 channel relative to the GE channel. Two key observations emerge.

904 First, the *redistribution channel* alone accounts for all the *qualitative effects* of
905 human capital adjustments on AI's aggregate impacts. Redistribution of human
906 capital increases consumption, even before AI implementation, as more households
907 shift to the high sector. It also reduces investment by mitigating precautionary
908 savings and lowers employment as middle-sector workers leave the labor market
909 to invest in human capital. In the long run, redistribution amplifies AI's positive
910 impact on output by reallocating more workers to sectors that benefit most from AI
911 advancements.

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

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

925 These observations lead to two key conclusions:

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

928 Second, the *GE channel*, when combined with human capital adjustment, qual-
929 itatively alters the effect of anticipating AI on the wealth Gini (as shown by com-
930 paring the blue lines in Figures ?? and ??).

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

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