Automation and Human Capital: Accounting for Individual-Level Responses

Daniil Kashkarov

CERGE-EI, Prague

EEA-ESEM CONGRESS 2022

- 1. Automation substitutes routine labour (production, clerks, sales) and complements abstract labour (managerial, professional)
- 2. Automation creates incentives...
 - ... for routine (R) workers to accumulate HC, to join abstract occupations
 - *in for abstract (A)* workers to accumulate more of HC
- 3. R workers can be limited in their mobility towards abstract occupations
 - lower learning ability/stock of HC.

- 1. Automation substitutes routine labour (production, clerks, sales) and complements abstract labour (managerial, professional)
- 2. Automation creates incentives...
 - ... for routine (R) workers to accumulate HC, to join abstract occupations
 - ... for abstract (A) workers to accumulate more of HC
- 3. R workers can be limited in their mobility towards abstract occupations
 - lower learning ability/stock of HC.

- 1. Automation substitutes routine labour (production, clerks, sales) and complements abstract labour (managerial, professional)
- 2. Automation creates incentives...
 - ... for routine (R) workers to accumulate HC, to join abstract occupations
 - ... for abstract (A) workers to accumulate more of HC
- 3. R workers can be limited in their mobility towards abstract occupations
 - lower learning ability/stock of HC.

- 1. Automation substitutes routine labour (production, clerks, sales) and complements abstract labour (managerial, professional)
- 2. Automation creates incentives...
 - ... for routine (R) workers to accumulate HC, to join abstract occupations
 - ... for abstract (A) workers to accumulate more of HC
- 3. R workers can be limited in their mobility towards abstract occupations
 - lower learning ability/stock of HC.

• Empirical Analysis:

- NLSY79 data: show ability-based selection to A and R occupations
- CPS data: estimate price series for A and R labor over the last 4 decades

Quantitative Analysis:

- Build life-cycle model with HC accumulation and occupational choice
- Calibrate it to NLSY79 cohort, using exogenous A and R price series (CPS)
- Run counterfactuals, fixing A and R prices on 1976 level
- See how HC responses to automation contribute to earnings inequality over the life cycle

• Empirical Analysis:

- NLSY79 data: show ability-based selection to A and R occupations
- CPS data: estimate price series for A and R labor over the last 4 decades

• Quantitative Analysis:

- Build life-cycle model with HC accumulation and occupational choice
- Calibrate it to NLSY79 cohort, using exogenous A and R price series (CPS)
- Run counterfactuals, fixing A and R prices on 1976 level
- See how HC responses to automation contribute to earnings inequality over the life cycle

From NLSY79 data:

- 1. Ability-based selection into R and A occupations
- 2. Over the life cycle, outflow of workers from R and inflow to A occupations
- 3. Probability of R \rightarrow A & A \rightarrow R switches is ability-dependent

From CPS data:

- 4. Price of R labor \downarrow and price of A labor \uparrow over the last 4 decades
 - Different from price series estimates for high-, mid-, and low-skilled labor

From NLSY79 data:

- 1. Ability-based selection into R and A occupations
- 2. Over the life cycle, outflow of workers from R and inflow to A occupations
- 3. Probability of R \rightarrow A & A \rightarrow R switches is ability-dependent

From CPS data:

- 4. Price of R labor \downarrow and price of A labor \uparrow over the last 4 decades
 - Different from price series estimates for high-, mid-, and low-skilled labor

What I find: Quantitative Analysis

1. Modest contribution of automation to log-earnings variance

- Up to 10.8% by the end of the working life cycle
- Mostly due to a change in prices for HC in R and A
- 2. Significant contribution of automation to abstract wage premium

 $\frac{avg(wage_A)}{avg(wage_R)} \uparrow = \frac{avg(Price_A \uparrow \times HC_A)}{avg(Price_R \downarrow \times HC_R)}$

- Up to 28.6% of a rise is due to automation
- 3. HC responses and $R \rightarrow A$ switches dampen a rise in abstract wage premium:

 $\frac{avg(wage_A)}{avg(wage_R)} \downarrow = \frac{avg(Price_A \times HC_A \downarrow)}{avg(Price_R \times HC_R \uparrow)}$

- The premium would be 35.5 p.p. higher in the absence of HC responses

What I find: Quantitative Analysis

- 1. Modest contribution of automation to log-earnings variance
 - Up to 10.8% by the end of the working life cycle
 - Mostly due to a change in prices for HC in R and A
- 2. Significant contribution of automation to abstract wage premium

 $\frac{avg(wage_A)}{avg(wage_R)} \uparrow = \frac{avg(Price_A \uparrow \times HC_A)}{avg(Price_R \downarrow \times HC_R)}$

- Up to 28.6% of a rise is due to automation
- 3. HC responses and $R \rightarrow A$ switches dampen a rise in abstract wage premium:

 $\frac{avg(wage_A)}{avg(wage_R)} \downarrow = \frac{avg(Price_A \times HC_A \downarrow)}{avg(Price_R \times HC_R \uparrow)}$

- The premium would be 35.5 p.p. higher in the absence of HC responses

1. Modest contribution of automation to log-earnings variance

- Up to 10.8% by the end of the working life cycle
- Mostly due to a change in prices for HC in R and A
- 2. Significant contribution of automation to abstract wage premium

 $\frac{avg(wage_A)}{avg(wage_R)} \uparrow = \frac{avg(Price_A \uparrow \times HC_A)}{avg(Price_R \downarrow \times HC_R)}$

3. HC responses and $R \rightarrow A$ switches dampen a rise in abstract wage premium:

 $\frac{avg(wage_A)}{avg(wage_R)} \downarrow = \frac{avg(Price_A \times HC_A \downarrow)}{avg(Price_R \times HC_R \uparrow)}$

- The premium would be 35.5 p.p. higher in the absence of HC responses

- Life-Cycle Inequality: Huggett, Ventura, and Yaron (2006, 2011), Storesletten, Telmer, and Yaron (2004)
 - This paper: workers with different ability/HC respond differently to automation
 - ...and this contributes to a rise in life-cycle earnings inequality
- Occupational Switching: Cortes (2016), Autor and Dorn (2009)
 - This paper: models the reasons underlying selection into A and R occupations
- Quantity vs. Price of HC: Bowlus and Robinson (2012), Heckman, Lochner, and Taber (1998)
 - This paper: shows that price series for HC in A and R diverge over time

- Empirical Analysis
- Model Description
- Calibration and Model Fit
- Counterfactual Experiments

Empirical Analysis

Ability-Based Selection

• AFQT scores from NLSY79 data

Ability-Based Selection

• AFQT scores from NLSY79 data

Occupational Distributions by Ability Quartiles

Ability-Based Selection

AFQT scores from NLSY79 data

Occupational Distributions by Ability Quartiles



- Ability predicts sorting across A and R occupations
 - $\,$ 45% of workers in A occupations are from the top ability quartile
 - 32% of workers in R occupations are from the lowest ability quartile
- AFQT scores still predict allocation to occupations after 2.5 decades

Occupational Switches

• Ability predicts switching between A and R occupations

Occupational Switches

• Ability predicts switching between A and R occupations

Occupational Switch Probabilities by Ability Quartiles

Occupational Switches

Ability predicts switching between A and R occupations

Occupational Switch Probabilities by Ability Quartiles



- More able agents are more likely to go to A occupations
 - Young least able are 7 times less likely to do RA switch than the most able ones
- Less able agents are more likely to fall to R occupations
- Switch probability decreases with age

Outflow of Workers from R Occupations

• Over the life cycle, net outflow from R to A occupations

Outflow of Workers from R Occupations

• Over the life cycle, net outflow from R to A occupations

Occupational share of R workers over the life cycle

Outflow of Workers from R Occupations

• Over the life cycle, net outflow from R to A occupations

Occupational share of R workers over the life cycle



- 19% fall in R workers share offset by a rise in A workers share
- R to A switchers earn more in 10 years than those staying R



Implications for the Effects of Automation:

- 1. Ability predicts individuals' capacity to adjust to automation
 - Less able agents are more limited in their upward mobility
- 2. High share of low-ability individuals in R occupations
 - Significant share is unable to respond to automation
- 3. High share of high-ability individuals in A occupations
 - Potentially accumulate more of human capital with automation
- 4. Workers upgrade from R to A occupations over the life cycle
 - Potentially dampens the effect of automation on earnings inequality

Implications for the Effects of Automation:

- 1. Ability predicts individuals' capacity to adjust to automation
 - Less able agents are more limited in their upward mobility
- 2. High share of low-ability individuals in R occupations
 - Significant share is unable to respond to automation
- 3. High share of high-ability individuals in A occupations
 - Potentially accumulate more of human capital with automation
- 4. Workers upgrade from R to A occupations over the life cycle
 - Potentially dampens the effect of automation on earnings inequality

Model Description

Model Description

Partial equilibrium, perfect foresight

- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for *J* periods
- Ex-ante heterogeneous in:
 - 1. Learning ability
 - 2. Initial HC in A occupation
 - 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

- Partial equilibrium, perfect foresight
- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for J periods
- Ex-ante heterogeneous in:
 - 1. Learning ability
 - 2. Initial HC in A occupation
 - 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

- Partial equilibrium, perfect foresight
- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for J periods
- Ex-ante heterogeneous in:
 - 1. Learning ability
 - 2. Initial HC in A occupation
 - 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

- Partial equilibrium, perfect foresight
- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for J periods
- Ex-ante heterogeneous in:
 - 1. Learning ability
 - 2. Initial HC in A occupation
 - 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

- Partial equilibrium, perfect foresight
- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for *J* periods

• Ex-ante heterogeneous in:

- 1. Learning ability
- 2. Initial HC in A occupation
- 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

- Partial equilibrium, perfect foresight
- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for *J* periods
- Ex-ante heterogeneous in:
 - 1. Learning ability
 - 2. Initial HC in A occupation
 - 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

- Partial equilibrium, perfect foresight
- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for *J* periods
- Ex-ante heterogeneous in:
 - 1. Learning ability
 - 2. Initial HC in A occupation
 - 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

- Partial equilibrium, perfect foresight
- Prices for R and A change exogenously
- Endogenous HC accumulation in A occupations, Ben-Porath type
- Agents living for *J* periods
- Ex-ante heterogeneous in:
 - 1. Learning ability
 - 2. Initial HC in A occupation
 - 3. Productivity in R occupation
- Time and monetary investment into human capital in A occupation
- HC stock in A and R hit by the idiosyncratic shocks
- Working in either A or R occupation

Agent's Problem

• Heterogeneous in learning ability a, R productivity η , and initial HC in A $h_{A,1}$
Agent's Problem

- Heterogeneous in learning ability a, R productivity η , and initial HC in A $h_{A,1}$
- Maximize lifetime utility, linear in consumption:

{

$$\max_{c_{j}, occ_{j}, l_{j}, n_{j}, d_{j}, h_{j+1}\}_{j=1}^{J}} E\left[\sum_{j=1}^{J} \beta^{j-1} c_{j}\right]$$
(1)

Model Description

Agent's Problem

- Heterogeneous in learning ability a, R productivity η , and initial HC in A $h_{A,1}$
- Maximize lifetime utility, linear in consumption:

$$\max_{[c_{j},occ_{j},l_{j},n_{j},d_{j},h_{j+1}]_{j=1}^{J}} E\left[\sum_{j=1}^{J} \beta^{j-1} c_{j}\right]$$
(1)

• Labor earnings go to consumption and monetary investment into $h_{A,r}$, (BC):

$$c_j + d_j = y_j \tag{2}$$

• Work in either A or R occupation:

$$y_j = P_{k,t}(exp(z_{k,j})h_{k,j}l_j), \text{ where } k \in \{A, R\}$$
(3)

Model Description

Agent's Problem

- Heterogeneous in learning ability a, R productivity η , and initial HC in A $h_{A,1}$
- Maximize lifetime utility, linear in consumption:

$$\max_{[c_{j},occ_{j},l_{j},n_{j},d_{j},h_{j+1}]_{j=1}^{J}} E\left[\sum_{j=1}^{J} \beta^{j-1} c_{j}\right]$$
(1)

• Labor earnings go to consumption and monetary investment into $h_{A,r}$, (BC):

$$c_j + d_j = y_j \tag{2}$$

Work in either A or R occupation:

$$y_j = P_{k,t}(exp(z_{k,j})h_{k,j}l_j), \text{ where } k \in \{A, R\}$$
(3)

- Note 1: the model follows one cohort over its life cycle.
- Note 2: automation is introduced through:
 - $P_{R,t} \downarrow$ and $P_{A,t} \uparrow$
 - $P_{R,t}$ and $P_{A,t}$ are time-dependent, not age-dependent

Occupational Choice and HC Accumulation

• The choice between occupations:

$$occ_j = A$$
 if $h_{A,j} \ge \frac{P_{R,t}exp(z_{R,j})}{P_{A,t}exp(z_{A,j})}h_{R,j}$ and $occ_j = R$ otherwise (4)

Occupational Choice and HC Accumulation

• The choice between occupations:

$$occ_j = A \text{ if } h_{A,j} \ge \frac{P_{R,t}exp(z_{R,j})}{P_{A,t}exp(z_{A,j})}h_{R,j} \text{ and } occ_j = R \text{ otherwise}$$
(4)

• Law of motion for $h_{A,j}$:

$$h_{A,j+1} = h_{A,j} + a(h_{A,j}n_j)^{\alpha_1}(d_j)^{\alpha_2}, \text{ where } \alpha_1 + \alpha_2 < 1$$
(5)

• Law of motion for $h_{R,j}$:

$$h_{R,j+1} = \eta f(j) \tag{6}$$

Occupational Choice and HC Accumulation

• The choice between occupations:

$$occ_j = A$$
 if $h_{A,j} \ge \frac{P_{R,t}exp(z_{R,j})}{P_{A,t}exp(z_{A,j})}h_{R,j}$ and $occ_j = R$ otherwise (4)

• Law of motion for $h_{A,j}$:

$$h_{A,j+1} = h_{A,j} + a(h_{A,j}n_j)^{\alpha_1}(d_j)^{\alpha_2}, \text{ where } \alpha_1 + \alpha_2 < 1$$
 (5)

• Law of motion for
$$h_{R,j}$$
:
 $h_{R,j+1} = \eta f(j)$ (6)

• Unit endowment of time in each period *j*:

$$l_j + n_j = 1 \tag{7}$$

Calibration and Model Fit

Calibration and Model Fit

• Estimate $P_{A,t}$ and $P_{R,t}$ using a "flat spot" approach

At older ages, changes in wages are due to changes in prices

 $\begin{aligned} & \text{Mean}[\text{In } h_{k,j+1,t+1}] = \text{Mean}[\text{In } h_{k,j,t}] \implies \text{Mean}[\text{In } P_{k,t+1}h_{k,j+1,t+1}] - \text{Mean}[\text{In } P_{k,t}h_{k,j,t}] \\ &= \text{In } P_{k,t+1} - \text{In } P_{k,t}, \text{ where } k \in \{A, R\} \end{aligned}$

- Applied to CPS data for 1976-2019; medians instead of means because of topcoding
- College grads aged 50-58 for A; high-school grads aged 46-55 for R

${\sf R}$ and ${\sf A}$ ${\sf Prices}$

- Estimate $P_{A,t}$ and $P_{R,t}$ using a "flat spot" approach
- At older ages, changes in wages are due to changes in prices

$$\begin{aligned} \text{Mean}[\ln h_{k,j+1,t+1}] = &\text{Mean}[\ln h_{k,j,t}] \implies \text{Mean}[\ln P_{k,t+1}h_{k,j+1,t+1}] - &\text{Mean}[\ln P_{k,t}h_{k,j,t}] \\ &= \ln P_{k,t+1} - \ln P_{k,t}, \text{ where } k \in \{A, R\} \end{aligned}$$
(8)

- Applied to CPS data for 1976-2019; medians instead of means because of topcoding
- College grads aged 50-58 for A; high-school grads aged 46-55 for R

- Estimate $P_{A,t}$ and $P_{R,t}$ using a "flat spot" approach
- At older ages, changes in wages are due to changes in prices

$$\begin{aligned} \text{Mean}[\ln h_{k,j+1,t+1}] = &\text{Mean}[\ln h_{k,j,t}] \implies \text{Mean}[\ln P_{k,t+1}h_{k,j+1,t+1}] - &\text{Mean}[\ln P_{k,t}h_{k,j,t}] \\ &= \ln P_{k,t+1} - \ln P_{k,t}, \text{ where } k \in \{A, R\} \end{aligned}$$
(8)

- Applied to CPS data for 1976-2019; medians instead of means because of topcoding
- College grads aged 50-58 for A; high-school grads aged 46-55 for R

- Estimate $P_{A,t}$ and $P_{R,t}$ using a "flat spot" approach
- At older ages, changes in wages are due to changes in prices

$$\begin{aligned} \text{Mean}[\text{In } h_{k,j+1,t+1}] = & \text{Mean}[\text{In } h_{k,j,t}] \implies \text{Mean}[\text{In } P_{k,t+1}h_{k,j+1,t+1}] - & \text{Mean}[\text{In } P_{k,t}h_{k,j,t}] \\ = & \text{In } P_{k,t+1} - & \text{In } P_{k,t}, \text{ where } k \in \{A, R\} \end{aligned}$$

$$(8)$$

- Applied to CPS data for 1976-2019; medians instead of means because of topcoding
- College grads aged 50-58 for A; high-school grads aged 46-55 for R

• Estimate $P_{A,t}$ and $P_{R,t}$ using a "flat spot" approach

• At older ages, changes in wages are due to changes in prices

$$\begin{aligned} \text{Mean}[\text{In } h_{k,j+1,t+1}] = & \text{Mean}[\text{In } h_{k,j,t}] \implies \text{Mean}[\text{In } P_{k,t+1}h_{k,j+1,t+1}] - & \text{Mean}[\text{In } P_{k,t}h_{k,j,t}] \\ = & \text{In } P_{k,t+1} - & \text{In } P_{k,t}, \text{ where } k \in \{A, R\} \end{aligned}$$

$$(8)$$

- Applied to CPS data for 1976-2019; medians instead of means because of topcoding
- College grads aged 50-58 for A; high-school grads aged 46-55 for R





• HC accumulation in R occupations: f(j) as age effect for R workers from PSID f(j)

- Number of lifetime periods J = 41, from real age of 18 to 58 and $\beta = 0.96$
- Initial conditions: $(h_0, a, \eta) \sim LN(\mu_x, \Sigma)$
- HC shock: i.i.d., $z_j \sim N(\mu, \sigma^2)$
- Calibrate initial distribution, shock, and α_1 , α_2 to match the moments from NLSY79:
 - 1. Variance of log-earnings
 - 2. Abstract wage premium
 - 3. Occupational distributions by ability quartiles
 - 4. Probabilities of RA and AR switches over age

parameters 🚺 Earnings Stats

- HC accumulation in R occupations: f(j) as age effect for R workers from PSID f(j)
- Number of lifetime periods J = 41, from real age of 18 to 58 and $\beta = 0.96$
- Initial conditions: $(h_0, a, \eta) \sim LN(\mu_x, \Sigma)$
- HC shock: i.i.d., $z_j \sim N(\mu, \sigma^2)$
- Calibrate initial distribution, shock, and α_1 , α_2 to match the moments from NLSY79:
 - 1. Variance of log-earnings
 - 2. Abstract wage premium
 - 3. Occupational distributions by ability quartiles
 - 4. Probabilities of RA and AR switches over age

parameters 🚺 Earnings Stats

- HC accumulation in R occupations: f(j) as age effect for R workers from PSID f(j)
- Number of lifetime periods J = 41, from real age of 18 to 58 and $\beta = 0.96$
- Initial conditions: $(h_0, a, \eta) \sim LN(\mu_x, \Sigma)$
- HC shock: i.i.d., $z_j \sim N(\mu, \sigma^2)$
- Calibrate initial distribution, shock, and α_1 , α_2 to match the moments from NLSY79:
 - 1. Variance of log-earnings
 - 2. Abstract wage premium
 - 3. Occupational distributions by ability quartiles
 - 4. Probabilities of RA and AR switches over age

parameters Earnings Stats

- HC accumulation in R occupations: f(j) as age effect for R workers from PSID f(j)
- Number of lifetime periods J = 41, from real age of 18 to 58 and $\beta = 0.96$
- Initial conditions: $(h_0, a, \eta) \sim LN(\mu_x, \Sigma)$
- HC shock: i.i.d., $z_j \sim N(\mu, \sigma^2)$
- Calibrate initial distribution, shock, and α_1 , α_2 to match the moments from NLSY79:
 - 1. Variance of log-earnings
 - 2. Abstract wage premium
 - 3. Occupational distributions by ability quartiles
 - 4. Probabilities of RA and AR switches over age

parameters 🚺 Earnings Stats

- HC accumulation in R occupations: f(j) as age effect for R workers from PSID f(j)
- Number of lifetime periods J = 41, from real age of 18 to 58 and $\beta = 0.96$
- Initial conditions: $(h_0, a, \eta) \sim LN(\mu_x, \Sigma)$
- HC shock: i.i.d., $z_j \sim N(\mu, \sigma^2)$
- Calibrate initial distribution, shock, and α_1 , α_2 to match the moments from NLSY79:
 - 1. Variance of log-earnings
 - 2. Abstract wage premium
 - 3. Occupational distributions by ability quartiles
 - 4. Probabilities of RA and AR switches over age

parameters Earnings Stats

Calibration and Model Fit

Earnings Stats and Ability Distributions



- U-shape of variance profile due to:
 - 1. High ability workers accumulating HC at the beginning of the life cycle
 - 2. High ability workers earning more later in the life cycle

RA mobility



RA mobility due to:

- 1. Medium to high a agents for whom $h_{A,j} \leq \frac{P_{R,t}h_{R,j}}{P_{A,t}}$ for the first *n* periods, but who invest into $h_{A,j}$ and switch to A in n + 1 period
- 2. Positive shocks to HC in A

AR mobility



- AR mobility due to negative realizations of HC shocks
- Ability-based selection due to strong positive a and $h_{A,1}$ correlation

Counterfactual Exercises

Counterfactual Exercises

Changes in HC Prices



• No automation: setting $P_{A,t} = P_{A,1976}$ and $P_{R,t} = P_{R,1976}$, $\forall t$

- Change in HC prices contribution:
 - Up to 10.8% to the variance Var Decomp
 - Up to 28.6% to the abstract wage premium

Contribution of HC responses



No HC response:

• Using estimated $P_{A,t}$, $P_{R,t}$, but keeping policies optimal under no change in prices

- HC responses and RA switches dampen a rise in abstract wage premium
- Without HC responses, abstract wage premium would be up to 35.5 p.p. higher

RA switches



With automation, RA mobility is higher across all ability quartiles

Across all ability quartiles — more intensive accumulation of HC in A (HC Response)

Conclusion

Empirical analysis

- Ability-based selection into R and A occupations
- Probability of RA and AR switches is ability-dependent
- $\bullet~$ Price of R $\downarrow~$ labor and A $\uparrow~$ labor over the last 4 decades
- Quantitative analysis
 - Modest contribution of automation to variance of log-earnings
 - Significant contribution of automation to abstract wage premium
 - HC responses and RA switches dampen a rise in the premium over life cycle

Appendix 1: NLSY79 Sample

Observations/Age	23-27	28-32	33-37	38-42	43-47	48-52	53-57	Total
Total	6,117	5,926	5,404	4,771	4,402	4,070	1,786	32,476
By shares of occ. categories Abstract Routine	0.27 0.63	0.34 0.58	0.38 0.54	0.41 0.50	0.42 0.48	0.43 0.47	0.45 0.46	0.37 0.54
Service	0.10	0.08	0.08	0.09	0.10	0.10	0.09	0.09

Table A1: NLSY79 Sample of Males by Age and Occupational Categories

Note: The table shows the number of observations and the shares of the three occupational categories by age groups for males from a cross-sectional sample of the NLSY79 data used for the analysis in this paper. Sample restrictions are: yearly working hours 260-5820 and yearly earnings at least \$1000 for those below 30 y.o., and yearly working hours 520-5820 and yearly earnings at least \$1500 for those above 30 y.o. (earnings are in 1979 dollars). Such restricted sample of males consists of 3,003 individual observations.



Labor Income of Switchers to A vs. Stayers in R

 Table A3.1: Labor Income across different Occupational Cycles

	Q1	Q2	Q3	Q4			
Panel 1: Routine Occupations Occ. upgrading (RRA and RAA) vs. staying (RRR)							
Occ.	0.226***	0.055	0.214***	0.247***			
upgrading	(0.056)	(0.042)	(0.032)	(0.038)			
Age	0.084***	0.035***	0.028**	-0.003			
	(0.027)	(0.012)	(0.012)	(0.011)			
Age^2	-0.001***	-0.001***	-0.001***	0.000			
	(0.000)	(0.000)	(0.000)	(0.000)			
Year	-0.001	0.026***	0.030***	0.014**			
	(0.007)	(0.005)	(0.004)	(0.006)			
Nonwhite	-0.033**	-0.011	0.020	-0.007			
	(0.015)	(0.015)	(0.026)	(0.033)			
Obs.	1736	2173	2165	1427			

Note: Columns Q1-Q4 show the estimated coefficients from a regression of log yearly labor income in t+10 on dummies for occupational upgrading and downgrading and a set of listed controls. Occ. upgrading dummy is defined as equal to 1 if individual follows RRA or RAA (upgrading) occupational cycle in t, t+2, and t+10, respectively and as equal to 0 if individual follows RRR (staying); Occ. downgrading dummy is defined as equal to 1 if individual follows AAR or ARR (downgrading) occupational cycle in t, t+2, and t+10, respectively and as equal to 0 if individual follows AAR or ARR (downgrading) occupational cycle in t, t+2, and t+10, respectively and as equal to 0 if individual follows AAA (staying). Robust s.e. in parentheses, *p < 0.1, **p < 0.05,

***p < 0.01 back

Labor Income of Switchers to R vs. Stayers in A

 Table A3.2:
 Labor Income across different Occupational Cycles

	Q1	Q2	Q3	Q4			
Panel 2: Abstract Occupations							
Occ0 227***0 267***0 285***0 475***							
downgrading	(0.116)	(0.064)	(0.045)	(0.050)			
Age	-0.055 (0.097)	0.086*** (0.026)	0.026 (0.017)	0.043*** (0.014)			
Age^2	0.001 (0.001)	-0.001*** (0.000)	-0.000 (0.000)	-0.001*** (0.000)			
Year	-0.004 (0.023)	0.020** (0.008)	0.012* (0.007)	0.024*** (0.004)			
Nonwhite	-0.047 (0.043)	-0.021 (0.033)	0.061*** (0.019)	-0.039 (0.026)			
Obs.	223	612	1577	2947			

Note: Columns Q1-Q4 show the estimated coefficients from a regression of log yearly labor income in t+10 on dummies for occupational upgrading and downgrading and a set of listed controls. Occ. upgrading dummy is defined as equal to 1 if individual follows RRA or RAA (upgrading) occupational cycle in t, t+2, and t+10, respectively and as equal to 0 if individual follows RRR (staying); Occ. downgrading dummy is defined as equal to 1 if individual follows AAR or ARR (downgrading) occupational cycle in t, t+2, and t+10, respectively and as equal to 0 if individual follows AAR or ARR (downgrading) occupational cycle in t, t+2, and t+10, respectively and as equal to 0 if individual follows AAA (staying). Robust s.e. in parentheses, *p < 0.1, **p < 0.05,

***p < 0.01 back

Counterfactual Exercises

Outflow from A occupations

- Longitudinal ASEC CPS data
- The lowest outflow from A is among college workers



- Share of A workers in t 1 observed out of A in t
- Out of A: R, S, unemployment, nilf back

Outflow from R occupations

• The lowest outflow from R is among high school workers



- Share of R workers in t-1 observed out of R in t
- Out of R: A, S, unemployment, nilf back

Inflow to A Occupations

The lowest inflow to A is among college workers



- Share of A workers in t observed out of A in t-1
- Out of A: R, S, unemployment, nilf back

Inflow to R Occupations

• The lowest inflow to R is among high school workers



- Share of R workers in t observed out of R in t-1
- Out of R: A, S, unemployment, nilf back

Wages of Stayers in A vs. Wages of those Joining/Leaving A

• Joining/Leaving A occupations do not statistically differ in wages from Stayers

Dep.: Log Hourly Wage	Col	Some Col	HS	Col	Some Col	HS
Year	0.005***	-0.000	0.000	0.005***	-0.002***	-0.002**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Joining A	-3.674	-0.746	5.616*			
	(4.123)	(3.541)	(2.995)			
Joining A $ imes$ Year	0.002	0.000	-0.003*			
	(0.002)	(0.002)	(0.001)			
Age	-0.003	0.000	0.003	-0.001	0.006**	0.010***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Leaving A				2.208	3.429	0.182
				(3.483)	(3.639)	(2.812)
Leaving A $ imes$ Year				-0.001	-0.002	-0.000
				(0.002)	(0.002)	(0.001)
Constant	-5.884***	3.645**	2.485	-6.447***	6.700***	5.485***
	(0.892)	(1.488)	(1.615)	(0.859)	(1.420)	(1.396)
Observations	21,648	8,624	6,777	22,206	8,944	7,020
R^2	0.011	0.006	0.002	0.009	0.007	0.004

Longitudinal ASEC CPS data

- Joining=1 if out of A in t 1 and in A in t; Joining=0 if in A in t 1 and in A in t
- Leaving=1 if in A in t 1 and out of A in t; Leaving=0 if in A in t 1 and in A in tback

Wages of Stayers in R vs. Wages of those Joining/Leaving R

• Joining/Leaving A occupations do not statistically differ in wages from Stayers

Dep.: Log Hourly Wage	Col	Some Col	HS	Col	Some Col	HS
Year	0.002*	-0.003***	-0.006***	0.001	-0.003***	-0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)
Joining R	2.274	1.582	-0.422			
	(4.611)	(2.969)	(2.108)			
Joining $R \times Year$	-0.001	-0.001	0.000			
	(0.002)	(0.001)	(0.001)			
Age	-0.011**	-0.007***	0.003*	-0.018***	-0.002	0.001
	(0.005)	(0.002)	(0.001)	(0.005)	(0.002)	(0.001)
Leaving R				-5.369	0.725	-1.925
				(5.414)	(2.889)	(2.272)
Leaving R $ imes$ Year				0.003	-0.000	0.001
				(0.003)	(0.001)	(0.001)
Constant	-0.975	8.906***	14.608***	2.059	9.481***	17.188***
	(2.604)	(1.312)	(0.757)	(2.821)	(1.347)	(0.755)
Observations	4496	10944	22552	4292	10997	23048
R^2	0.007	0.004	0.013	0.016	0.004	0.017

- Joining=1 if out of R in t 1 and in R in t; Joining=0 if in R in t 1 and in R in t
- Leaving=1 if in R in t 1 and out of R in t; Leaving=0 if in R in t 1 and in R in tback

Age Profile in R occupations



 $log(y_{age,t}) = \beta_0 + \beta_1 age + \beta_2 age^2 + \gamma_1 t + \gamma_2 t^2 + \epsilon_{j,t}$ $f(j) = \beta_0 + \beta_1 j + \beta_2 j^2 = -1.09 + 0.1523j - 0.0017j^2, \text{ where } j \in [18, 68]$

No shocks



RA mobility in the data vs. mobility in the model


A and R Ability Distributions









Table: Variance of log-Earnings in the Models with Different Sources of Earnings Variation

	Age			
Model	25	35	45	55
Full Model	0.64	0.36	0.59	0.69
No growth in Prices	0.59 (0.92)	0.38	0.54 (0.91)	0.62 (0.89)
No shocks	0.54 (0.85)	0.19 (0.53)	0.46	(0.03) 0.54 (0.78)
No variation in initial conditions	0.09 (0.14)	0.09 (0.24)	0.13 (0.2)	0.18 (0.26)

Note: Full model – the baseline calibration; No growth in prices – prices for human capital in abstract and routine occupations are fixed at the 1979 level; No shocks – the variance of shocks to human capital in abstract and routine occupations is set to 0; No variation in initial conditions – a, $h_{A,j}$, and η are set to the mean values of the calibrated distributions for all agents. Values in brackets show the share of the Full model variance produced by each model.



Counterfactual Exercises

Calibration: Empirical Moments



Each line is using age effects β_j from: $stat_{j,t} = \mu^{stat} + \alpha_c^{stat} + \beta_j^{stat} + \epsilon_{j,t}^{stat}$

Calibration: Parameter Values

Definition	Symbol	Value		
Discount factor	β	0.9615		
Length of the life cycle	J	41		
Abstract HC prices	$P_{A,j}$	[1, 1.18]		
Routine HC prices	$P_{R,j}$	[0.80, 1]		
Age premium in routine job	f(j)	$f(j) = -1.09 + 0.1523j - 0.0017j^2$		
HC elasticities	α_1 , α_2	0.61, 0.15		
Initial conditions	$(h_0, a, \eta) \sim LN(\mu_x, \Sigma)$	$ \begin{pmatrix} \mu_h, \mu_a, \mu_\eta \end{pmatrix} = (4.77, -1.50, 5.23); \\ \begin{bmatrix} \sigma_h^2 & \sigma_{ha} & \sigma_{h\eta} \\ \sigma_{ah} & \sigma_a^2 & \sigma_{a\eta} \\ \sigma_{\eta h} & \sigma_{\eta a} & \sigma_\eta^2 \end{bmatrix} = \begin{bmatrix} 0.62 & 0.19 & 0.33 \\ 0.19 & 0.29 & 0.14 \\ 0.33 & 0.14 & 0.55 \end{bmatrix} $		
Abstract HC shocks	$z \sim N(\mu_A, \sigma_A^2)$	$(\mu_A, \sigma_A) = (0, 0.07)$		
Routine HC shocks	$z \sim \textit{N}(\mu_R, \sigma_R^2)$	$(\mu_R,\sigma_R)=(0,0.09)$		
Price ratio in j=1	P _{R,1976} /P _{A,1976}	0.70		



HC Responses Across Ability Quartiles

