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RBTC and Human Capital: Accounting for Individual-Level Responses

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RBTC and Human Capital: Accounting for Individual-Level Responses*

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Abstract

I test the contribution of individual human capital responses to earnings inequality arising in the process of the routine-biased technological change (RBTC). I develop a life-cycle model of human capital and occupational choice, calibrate it to the NLSY79 data, using the price series for human capital in abstract and routine occupations estimated from the cross-sectional CPS data with the "flat spot" approach. I then use the model to quantify the effect of a change in human capital prices on earnings inequality. I find that an increase in the price for human capital in abstract occupations and a fall in its price in routine occupations associated with RBTC has a modest contribution to the evolution of variance of log-earnings — up to 10.8 per cent by the end of the working life cycle. However, the contribution of RBTC to an increase in the abstract wage premium over the lifetime of the NLSY79 cohorts is up to 28.6 per cent. The growth of the abstract wage premium is significantly dampened by the human capital responses of workers switching from routine occupations.

JEL classification: J24,J31,D15,O33

Key words: RBTC, human capital, life-cycle modelling, NLSY79, AFQT.

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1 Introduction

In the last decade, the economic literature studying the effects of routine-biased technological change (RBTC) on general production patterns has witnessed rapid development (Acemoglu and Autor, 2011; Sachs and Kotlikoff, 2012; Autor and Dorn, 2013; Sachs et al., 2015; Acemoglu and Restrepo, 2018a). Due to the labour-replacing nature of RBTC, researchers in the field have focused on its implications for labour markets. In this respect, the main concern of a part of the academic community, as well as of the general public, has been the tendency to automate tasks that were previously performed by human labour. For instance, Acemoglu and Restrepo (2018b), in their empirical study of industrial robot penetration in the US, find a robust negative effect on employment and wages associated with the introduction of labour-replacing technology. Autor et al. (2006), Goos and Manning (2007), and Autor and Dorn (2013) argue that RBTC is responsible for massive reallocations of labour from middle-skill occupations to high- and low-skill occupations.

While current studies mostly attempt to identify the direct consequences of RBTC, including reallocations of the labour force and changes in wage schedules, less attention has been dedicated to the consequences of the responses of individual workers to the (dis)incentives created by this kind of technological change[1]. In particular, the possibility to adjust human capital in response to RBTC gives rise to several channels through which the distribution of earnings can be affected. The capital-skill complementarity relationship (Krusell et al., 2000; Autor et al., 2003) implies that one way for workers to mitigate the possible impacts of RBTC at the individual level is to accumulate human capital through education or on-the-job training, which allows them to supply more sophisticated types of labour. Individuals possessing high levels of human capital absorb the benefits created by technological change in high-skill occupations. In contrast, individuals with lower levels of human capital who are unable to accumulate it in sufficient amounts are expected to bear the losses associated with the replacement of middle-skill occupations in the course of RBTC. Autor and Dorn (2009) show that workers who have a college degree, and thus possess a higher stock of human

[1] A notable exception is the recent paper by Cavounidis and Lang (2020) where the authors, using the model with investment into multiple skills, rationalize the differences in the capacity to adjust to unexpected technological shocks for younger and older workers.

capital, are able to relocate from middle- to high-skill occupations. Lower human capital agents are more likely to relocate to low-skill occupations, non-employment or to remain in middle-skill occupations that are gradually disappearing (Autor and Dorn, 2009; Cortes, 2016; Cortes et al., 2017).

The aptitude to augment an individual's stock of human capital is dependent on education and learning ability. Huggett et al. (2006; 2011), using the PSID data, show that differences in learning ability and initial human capital (including education) on entry into the labor market are responsible for the major part of the variation in lifetime earnings. Differences in learning ability are driving the evolution of earnings dispersion over the life cycle (Huggett et al., 2006). In the context of technological change, these differences in learning ability would translate into the variation in the capacity to accumulate human capital in response to RBTC and potentially contribute to changes in the distribution of earnings.

A recent cross-country analysis conducted by (PricewaterhouseCoopers, 2018), which is in line with the results obtained by Frey and Osborne (2017) and Acemoglu and Restrepo (2018b), suggests that the risk of replacement by technology is the most pronounced for the individuals with low levels of education. These are workers often employed in occupations classified as *routine*, e.g., manufacturing, administration and support services. Routine occupations are characterized by a set of well-defined, often repetitive, tasks that can be to a high extent automated through computerization and robotization. This is a group of occupations responsible for a decrease in employment in middle-skilled occupations (Acemoglu and Autor, 2011). Cortes (2016) demonstrates on the PSID data the presence of ability-based selection out of the routine occupations, with lower ability agents having lower chances to join *abstract* occupations. Abstract occupations, e.g., engineers or managers, require non-standard thinking, perpetual learning, adaptability and high level of skill/human capital. This group of occupations is considered to be complemented by technology and has experienced a dramatic rise in wages over the last decades (Acemoglu and Autor, 2011).

In this paper I acknowledge the fact that RBTC creates incentives for individuals to enter the abstract occupations in order to benefit from the rising returns on working in them. This kind of individual response is akin to an increase in college attainment in the context of traditional skill-biased technological change (among recent contributions are Kong et al.

(2018), and Donovan and Herrington (2019)). For the individuals employed in abstract occupations, an increase in the productivity of human capital motivates them to further augment their personal human capital stock. At the same time, individuals with low learning ability and/or stock of human capital find it relatively more costly to accumulate human capital and can be constrained in their capacity to enter abstract occupations and benefit from RBTC. With such individuals having lower opportunities to enter abstract occupations, a situation occurs when the benefits from the technological change are predominantly accrued to the individuals with higher ability and human capital, while those with less favorable conditions remain constrained in their mobility towards abstract occupations. This uneven allocation of the benefits created by RBTC may further amplify the mechanism driven by heterogeneity in ability and human capital described by Huggett et al. (2006) and can contribute to a rise in the dispersion of earnings over the working life cycle.

The aim of this study is to test the contribution of a change in prices for human capital in routine and abstract occupations, and the resulting individual human capital responses over the working life cycle, to the earnings inequality arising from the process of RBTC. It must be mentioned that potentially RBTC is not the only factor contributing to changes in prices for human capital in abstract and routine occupations. As pointed out by Autor et al. (2013), international trade and offshoring can also contribute to changes in income and employment shares of routine workers. Firpo et al. (2011) suggest that offshoring played a role in wage polarization for US males in the 2000s. However, a larger body of literature provides support for RBTC being the main source for the changes observed in demand for routine labour (Goos and Manning, 2007; Autor and Dorn, 2013; Michaels et al., 2014). In this paper I turn to the latter larger strand of the literature in investigating and interpreting the changes in human capital prices, implied human capital responses and resulting earnings inequality. At the same time, the model developed in this paper remains largely agnostic about the underlying reasons for changes in prices for human capital in abstract and routine occupations, with RBTC and offshoring being equivalent both observationally and in terms of implications for the earnings inequality within the model.

The paper proceeds as follows. Section 2 describes the main source of data used in this paper – the National Longitudinal Survey of Youth 1979 (NLSY79). It further provides the reader with some micro evidence suggesting the presence of ability-based selection into abstract and routine occupations that persists over the working life cycle. The degree of mobility between routine and abstract occupations is ability dependent, with the less-able agents having lower opportunities to switch to abstract occupations over the working life cycle. Based on the micro evidence described in Section 2, Section 3 develops a life-cycle model featuring agents with different abilities and human capital endowments who make dynamic decisions about the accumulation of additional human capital and choose between employment in abstract and routine occupations. Section 4 uses cross-sectional CPS data to estimate the price series for human capital in routine and abstract occupations. Section 5 describes the calibration of the model developed in Section 3 and discusses its fit to the data. Section 6 runs the counterfactual exercises that are used to establish the effect of a change in prices of human capital in abstract and routine occupations on the evolution of variance of log-earnings and the abstract wage premium, over the working life cycle of the NLSY79 cohorts.

2 Data and Micro Evidence

2.1 NLSY79 Data and Sample Restrictions

The main source of data used in the analysis is the National Longitudinal Survey of Youth 1979 (NLSY79). This is a representative panel of US cohorts aged from 16 to 24 in 1981, with the latest release in 2018. Using data on the three-digit occupational codes in the NLSY79, all occupations can be mapped into three broad categories, in accordance with the classification developed by Acemoglu and Autor (2011). These broad categories are: (1) Abstract (non-routine cognitive), e.g., financial, management and technical occupations. Abstract occupations are considered to benefit from RBTC; (2) Routine, e.g., sales and administrative workers, craftsmen and laborers. Routine occupations are considered to be gradually replaced by technology, due to their repetitive algorithmic nature; (3) Service occupations (non-routine manual), e.g., cleaners, waiters and health trainees. Since the main focus of the paper is on the transitions between routine and abstract occupations, most of the statistics reported are for these two broad occupational categories. It should also be mentioned that the share of service workers in all the releases of the NLSY79 is relatively small. Additionally, most occupational mobility takes place between the first two occupational categories, without an apparent increase or decrease in the share of service workers over the lifetime of the NLSY79 cohorts[2]. If an individual reports more than one occupation in a particular year, the broad category corresponding to the occupation with the longest hours is assigned to the individual in that year.

This paper uses males aged 23-57 from the cross-sectional sample of the NLSY79[3]. The lower bound for the age restrictions is motivated by the fact that for males younger than 23 the occupational data is either largely missing or shows the signs of miscoding. For the upper bound, as the set of NLSY79 cohorts is approaching retirement age, the number of observations starts to fall rapidly, yielding imprecise estimates of the earnings statistics after the age of 57. Further, the sample is restricted to the observations with yearly working hours between 260 and 5820 for those under 30, and between 520 (a quarter of full-time work hours) and 5820 for those over 30. Individuals under 30 are required to earn at least \$1000 a year, while those over 30 are required to earn at least \$1500. All earnings are in 1979 prices. Restrictions on hours and earnings are associated with the specification of the model used in this paper, in which there only two forms of time usage: either working or learning (accumulating human capital). For workers under 30, hours and earnings restrictions are lowered to allow for the possibility of a part-time job while studying.

Table A.1 in the appendix shows the sizes of the restricted sample of NLSY79 males and the respective shares of broad occupational categories across different age groups. A

[2]A rise in the share of service workers has mostly been demonstrated on the cross-sectional data (Autor and Dorn, 2009, 2013; Cortes et al., 2017). Based on the panel data, since the late 1970s, the probability of switching from routine to abstract occupations has increased more than to service occupations (Cortes, 2016; Jaimovich and Siu, 2014). Overall, the probability of switching from routine to abstract occupations is higher for all ability levels than for service occupations (Cortes, 2016).

[3]The NLSY79 cross-sectional sample keeps track of a representative sample of non-institutionalized civilian young people born between 1957 and 1964. Two other samples are designed to: (1) oversample civilian Hispanic/Latino, black, or economically disadvantaged youth; and (2) represent the population serving in the military. The analysis in the paper is conducted on the cross-sectional sample.

sample satisfying all the restrictions consists of 32,476 occupational observations for 3,003 individuals. There are a total of 12,016 and 17,537 occupational observations in abstract and routine occupations, respectively. As mentioned above, the share of service occupations is relatively small and does not exhibit any clear upward or downward movement over the working life cycle of the NLSY79 cohorts[4]. In contrast, the share of abstract workers gradually increases over the working life cycle as the workers from routine occupations switch to abstract occupations.

In addition to the standard individual-level data, including yearly income, working hours and education, the NLSY79 data features the scores from the Armed Forces Qualification Test (AFQT). The AFQT is a cognitive test that is widely used as a measure of ability (see, for example, Hendricks and Schoellman (2014) and Donovan and Herrington (2019). The availability of the measure of ability in the NLSY79 data makes it possible to reconcile the ability-based predictions of the structural model described below with the labour market outcomes observed in the data.

2.2 Ability and Relocation of Labour between Routine and Abstract Occupations

Individuals from the NLSY79 data were entering their prime age and were already actively participating on the labour markets in between the 1980s and the beginning of the 2000s. This period in US history was marked by a declining employment share for routine occupations and an increasing wage premium for non-routine (abstract and service) occupations (Autor and Dorn, 2013; Eden and Gaggl, 2018). These labour market trends are commonly attributed to the onset of RBTC and were accompanied by rapidly-falling costs of performing standardized computations (Nordhaus, 2007) and by a growing ICT capital income share (Eden and Gaggl, 2018). Therefore, while keeping track of a relatively narrow set of cohorts, the NLSY79 includes observations for individuals who were making their decisions in an

[4]The upward trend in the share of service workers is potentially offset by a stronger upward trend in the share of abstract workers. Another reason is related to the earnings restrictions applied to the data: service occupations, clustered at the lower end of the earnings distribution, often fall below the lower bound of yearly earnings.

economy transitioning towards lower use of routine labour. In other words, the NLSY79 cohorts were among those exposed to the initial effects of RBTC and had to behave in accordance with the rapidly changing labour market conditions.

Based on the subsample of the NLSY79 data described in the previous section, I calculate a set of statistics intended to show that the relocation of workers from routine to abstract occupations is dependent on ability and likely to be associated with a gradual accumulation of human capital for a subset of workers observed in routine occupations earlier in the working life cycle. In the context of RBTC, this would mean that a subset of routine workers is not only disadvantaged by the labor-replacing nature of the technological change, but also experiences less opportunity to adjust to it by relocating to abstract occupations. A growing disparity between less-able workers in routine occupations on the one side, and more-able workers in abstract occupations (those who find it efficient to accumulate additional human capital in response to automation) on the other side, would then potentially contribute to earnings inequality over the working life cycle.

Figure 1 shows the distributions of individuals by ability quartiles in abstract and routine occupations, as measured by their AFQT scores. The distributions are calculated for individuals aged 25 and 50. By the age of 25 the majority of young males have already entered the labor market (occupational codes are available for a large share of the sample), while by the age of 50 the mobility across occupations falls significantly in the NLSY79 data, and the occupational distributions become virtually constant. In other words, occupational distributions as of age 25 and 50 are chosen to approximate the sorting into abstract and routine occupations at the beginning and end of the working life cycle.

Ability-based selection is observed for both abstract and routine occupations. The share of workers employed in abstract occupations is rising in ability and the share of workers in routine occupations is falling in ability, i.e., more-able individuals tend to be employed in abstract occupations, while routine occupations accommodate more of the less-able individuals. This pattern is observed for both initial (at age 25) and final (at age 50) occupational distributions. Note, that, although the AFQT was administered when individuals were aged from 16 to 24, it still predicts their allocation to different occupations several decades later. This suggests that the AFQT scores measure some of the fundamental and largely immutable cognitive characteristics that define the performance of individuals throughout a significant part of their lifetime.

A high share of low ability individuals in routine occupations at the beginning and end of the working life cycle suggests that, when exposed to the effects of RBTC, a significant share of routine workers might be incapable of joining abstract occupations. In the course of the working life cycle, the AFQT-based measure of ability predicts the probability of routine-to-abstract (RA) and abstract-to-routine (AR) occupational switches. The left panel of Figure 2 shows that the probability of switching from a routine to abstract occupation (calculated as the probability of changing occupation between period t and $t+2$) is larger for individuals with higher ability. This pattern holds true for different age intervals (25-34, 35-44 and 45-54), with the overall probability of RA switches falling over age. The right panel of Figure 2 shows the probabilities of AR switches. Less able agents in abstract occupations are more likely to switch to routine occupations, than their more able counterparts. In general, Figure 2 suggests that during RBTC, as conditions in routine occupations deteriorate, more-able agents in routine occupations would demonstrate a higher capacity to adjust to the changes on the labor market by switching to abstract occupations. For lower ability agents there is less opportunity for adjustment and, even if they manage to enter the abstract occupations, there are higher chances for them falling back into routine occupations.

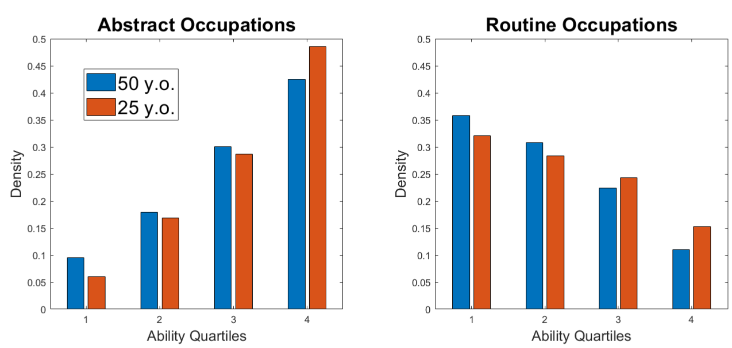

Figure 1: Occupational Distributions by Ability Quartiles

Note: Figure 1 plots the distribution of individuals in routine and abstract occupations by ability, as measured by their AFQT scores. All individuals aged 25 and 50 with non-missing observations for broad occupational categories (either routine or abstract) are divided into ability quartiles. Ability measures are cleaned from the age effects: AFQT scores are regressed on the age when individuals were tested (16-24), and the residuals are used as the measures of ability.

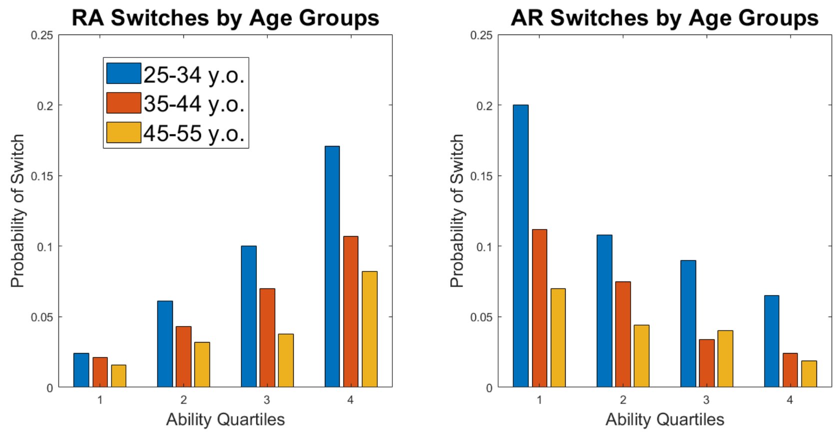

Figure 2: Occupational Switch Probabilities by Ability Quartiles

Note: The probabilities of a switch are calculated as the share of individuals aged j in year t from ability quartile q who in period $t+2$ are observed in a broad occupational category different from that in which they were observed in year t. The probabilities are calculated on the subsample of individuals who have valid occupational observations in years t and $t+2$. Definition of the switches on the two-year intervals is due to the NLSY79 becoming biannual after 1994. Service workers are excluded from the subsample.

Table 1 sheds some light on the long-run occupational paths in the NLSY79 data by comparing the workers who switch from routine occupations between years t and $t+2$ to those who remain in routine occupations over the same period. For each ability quartile, the table shows the shares of workers by the occupations in which they are observed in $t+10$, conditional on either switching or staying in a routine occupation in year $t+2$. With a rise in the workers' ability, the share who follow the RAA path, i.e., starting in a routine occupation in t, switching to an abstract occupation by $t+2$ and ending up in an abstract occupation in $t+10$, increases relative to the share who follow the RAR path (switching to abstract by $t+2$ and falling back to routine by $t+10$). This is in line with Figure 2, which shows the higher probabilities of falling back to routine occupations for low ability routine workers who managed to switch to abstract occupations at some point over the working life cycle.

Mobility across routine and abstract occupations over the working life cycle contributes to the differences in ability-based selection between the initial and final occupational distributions. As can be seen from Figure 1, the initial distribution for abstract occupations exhibits steeper ability-based selection than the final one. The opposite holds true for routine occupations. In addition to the selection out of the sample, these differences in the degrees of ability-based selection at the beginning and towards the end of the working life cycle are largely driven by the net occupational mobility from routine occupations. Table 1 shows that the majority of those who switch their occupation in the long run, are following either RAA or RRA paths. Such occupational paths are observed across all ability quartiles and a share of individuals who upgrade from routine to abstract occupations throughout the working life cycle dampens the selection in the final ability-based distribution in abstract occupations. On the other hand, the fact that the probability of occupational upgrading is rising in ability, increases the share of lower-ability agents in routine occupations towards the end of the working life cycle.

Table 1: Occupational Paths for Routine Workers (by Ability Quartiles)

Occupation in period:			**Fraction of workers(%):**			
(t)	**(t+2)**	**(t+10)**	**Q1**	**Q2**	**Q3**	**Q4**
R	A	A	1.0	3.0	6.7	13.9
R	R	A	4.1	10.4	12.7	21.7
R	R	R	84.8	78.6	71.7	56.5
R	A	R	1.3	2.1	2.5	4.0
R	S	R	1.8	1.4	1.4	0.8
R	S	A	0.3	0.3	0.7	0.4
R	A	S	0.2	0.3	0.3	0.1
R	S	S	1.6	0.9	1.0	0.8
R	R	S	4.9	3.0	2.9	1.7

Note: R-routine occupation, A-abstract occupation, S-service occupation. First three columns show the periods in which observations of occupational category are taken for each individual: in a current year, in two years and in 10 years. The last four columns show the fractions of workers from different ability quartiles following a particular occupational path. Probabilities of the occupational paths are calculated in the same manner as the probabilities of switching categories for Figure 2. Here, the observations in service occupations are also included.

Table A.2 in the Appendix also shows that the reverse pattern for the long-run occupational mobility holds true for abstract occupations: the probability of being observed in a routine occupation in 10 years is falling with ability. The mobility from abstract occupations partially offsets the selection effect of mobility from routine occupations on the final occupational distributions. However, as can be seen from Table A.1, the share of abstract workers in all periods is lower than that of routine workers, making the flow from abstract occupations smaller in absolute terms than that from routine occupations.

The occupational paths of the RAA or RRA type generally represent cases of occupational upgrading. Table A.3 in the appendix compares the labor income at the end of the occupational path for those who changed occupation with those who remained in the occupational category in which they started the path. As follows from Panel 1, the labor income 10 years after being observed in a routine occupation is higher for those individuals who follow the RRA and RAA paths, than for those who remain in a routine occupation. This holds true across all the ability quartiles. In this context, the RAA and RRA paths can be rationalized by a gradual accumulation of human capital necessary for employment in abstract occupations. Such occupational path is considerably more likely for individuals with higher ability. At the same time, as suggested by Panel 2 of Table A.3, individuals switching from abstract occupations and following the AAR and ARR occupational paths find themselves earning less than those staying in A occupations. This occupational downgrading is more likely for less-able individuals.

Overall, the features of the ability-based selection into abstract and routine occupations suggest that ability, as measured by the AFQT scores, is predictive individuals' capacity to adjust to RBTC: less-able agents are more limited in the opportunities for upward mobility towards abstract occupations. Together with the fact that the share of individuals with lower ability in routine occupations is relatively high, this creates conditions under which a significant share of routine workers is potentially unable to respond to technological change by accumulating the human capital necessary to enter abstract occupations. At the same time, abstract occupations accommodate more of the individuals with high ability who are potentially able to respond to a rise in returns on human capital in abstract occupations by augmenting their own stock of human capital. Limited capacity for adjustment on the side of routine workers and a high share of highly-able workers accumulating human capital in abstract occupations has the potential to contribute to inequality in lifetime earnings. Individuals observed in routine occupations earlier in the working life cycle who switch to abstract occupations later on can potentially mitigate the adverse effects of RBTC on earnings inequality. However, the share of such switchers also falls in ability and, even conditional on performing the RA switch, the probability of remaining in an abstract occupation over the longer term is lower for less able individuals.

3 Model of Human Capital Investment and Occupational Choice

For the analysis of the effects of RBTC on individual decisions about the accumulation of human capital I introduce two types of labour, routine and abstract, into a human capital model developed in the spirit of Huggett et al. (2006; 2011). Optimization problem 1 defines the decisions made by the agents in the model. Agents live for J periods and maximize the present value of their consumption. In each period, the labor income y_j is divided between consumption c_j and monetary investment into human capital in abstract occupation d_j. Labor income in each occupation is defined as the product of the price of human capital $P_{k,t}$ (price per efficiency unit of labor), the stock of human capital $h_{k,j}$, and working time l_j. Agents allocate a unit endowment of time in each life-cycle period j between working in either an abstract or routine occupation and learning time n_j. In each period, the stocks of human capital in abstract and routine occupations are hit by the idosyncratic zero-mean shocks $z_{A,j}$ and $z_{R,j}$.

$$\max_{\{c_j, occ_j, l_j, n_j, d_j, h_{j+1}\}_{j=1}^{J}} \mathbb{E}_0 \left[\sum_{j=1}^{J} \beta^{j-1} c_j \right] \tag{1}$$

$$\text{s.t.}$$

$$c_j + d_j = y_j$$
$$y_j = P_{k,t}(exp(z_{k,j}) h_{k,j} l_j), \text{ where } k \in \{A, R\}$$
$$l_j + n_j = 1$$

Changes in the prices for human capital in abstract occupation $P_{A,t}$ and in routine occupation $P_{R,t}$ are used to introduce the effect of RBTC into the model. Note that both $P_{A,t}$ and $P_{R,t}$ are indexed by the years t and not by the life-cycle periods j. This is to reflect the fact that changes in human capital prices are time-dependent, and are not age dependent. In the following sections, the calibrated model is simulated for the NLSY79 cohorts, treated as one cohort to increase the number of observations. The agents from this cohort will be making decisions about the accumulation of human capital over the working life cycle, taking human capital prices changing over years as exogenously given.

Changes in prices for human capital alter the decisions of agents regarding the amount and type of labour supplied. Agents choose to supply abstract or routine labour based on their comparative advantage, in the tradition of Roy (1951). Inequality 2 must hold for the agent to supply abstract labour. Abstracting from the human capital shocks, price-adjusted productivity in a routine occupation should be lower than the productivity in an abstract occupation for the agent to choose an abstract occupation. Changes in relative prices affect the decisions of agents by: (1) increasing/lowering the threshold for an occupational switch defined by Inequality 2; (2) changing the returns to monetary and time investment into human capital in an abstract occupation.

$$h_{A,j} \geq \frac{P_{R,t}}{P_{A,t}} \frac{exp(z_{R,j})}{exp(z_{A,j})} h_{R,j} \tag{2}$$

Equations 3 and 4 define the laws of motion for the stocks of human capital in abstract and routine occupations. Similarly to Huggett et al. (2006; 2011), individual agents start their J-period lives with the draws of initial human capital in abstract occupation $h_{A,1}$ and ability a, differing across the agents. Human capital accumulation in abstract occupations is of a Ben-Porath (1967) type. As follows from Equation 3, to extend the stock of human capital in an abstract occupation, the current stock of human capital in abstract occupation $h_{A,j}$ is combined with learning time n_j and a share of consumption good d_j in a human capital production function of a Cobb-Douglas form with elasticities α_1 and α_2. Ability a affects the slope of the human capital production function, i.e., the speed with which human capital in abstract occupations can be accumulated.

From Equation 4, human capital in routine occupations is set to follow function $f(j)$, which captures the evolution of earnings over the working life cycle of a routine worker and can be regarded as the age premium in the routine occupation. An additional initial condition

η is associated with the productivity in the routine occupation, shifting the earnings profile $f(j)$ up or down.

$$h_{A,j+1} = h_{A,j} + a(h_{A,j}n_j)^{\alpha_1}(d_j)^{\alpha_2},\ where\ \alpha_1 + \alpha_2 < 1 \tag{3}$$

$$h_{R,j+1} = \eta f(j) \tag{4}$$

Lifetime occupational choices, and implied earnings, depend on the realizations of initial conditions $(a, h_{A,1}, \eta)$. The realizations of $h_{A,1}$ can be such that an agent finds it optimal to work in an abstract occupation from the first period of the working life cycle, i.e., the condition in Inequality 2 is satisfied from $j = 1$. At the same time, with sufficiently low realizations of a and $h_{A,1}$ and/or high productivity in routine occupation η, a portion of agents choose to work in routine occupations in the course of all J periods.

There is, however, an intermediate case in which the realizations of $h_{A,1}$ and a are such that an agent optimally chooses to work in a routine occupation for the first $(s-1)$ periods, while simultaneously accumulating human capital stock in an abstract occupation to switch to it in period s. For instance, such a scenario is possible with a low realization of $h_{A,1}$ and high realization of a. In that case, although starting the working life cycle with insufficient human capital to work in an abstract occupation, an agent is able to relatively quickly accumulate the necessary human capital and to switch from a routine to an abstract occupation in later periods.

Agents who work in an abstract occupation from the beginning of the working life cycle (or switch to one later in life) set optimal amounts of d_j and n_j so that the loss of the expected lifetime consumption from expending an additional unit of n_j or d_j in period j is equal to the gain from the higher expected stock of human capital in the next period (or in the periods following the switch to an abstract occupation). Agents who optimally choose to work in a routine occupation during the whole life cycle make no human capital investments and inelastically supply their unit endowment of time in a routine occupation.

4 Price Series for Human Capital in Abstract and Routine Occupations

4.1 "Flat Spot" Approach

The application of models with endogenous human capital accumulation, including the one developed in this paper, is associated with the well-known problem of underidentification. It follows from the equation defining the y_j in Optimization problem 1 that, over the working life cycle, changes in individual's earnings can be attributed to either changes in the price of human capital $P_{k,t}$ or in the stock of an individual's human capital $h_{k,j}$. While the product of $P_{k,t}$ and $h_{k,j}$ can be observed in the data as the individual's hourly wage, $P_{k,t}$ and $h_{k,j}$, cannot, in general, be separated from each other. At the same time, since the partial equilibrium model described in the previous section takes the prices of human capital as exogenously given and has human capital accumulated endogenously over the working life cycle, it is important to be able to estimate the price series for human capital separately from the changes in human capital stock.

In order to identify the price series of human capital from the wage data, this paper adapts a "flat spot" approach, first suggested by Heckman et al. (1998) and developed further by Bowlus and Robinson (2012). Under the "flat spot" approach, the identification of the human capital price $P_{k,t}$ comes from the property of the Ben-Porath (1967) type models whereby the stock of human capital is constant towards the end of the working life cycle. In the context of the model used in this paper, the agents augment their stock of human capital in an abstract occupation only up to the point when the cost of production of an additional unit of human capital is equal to the expected remaining lifetime benefit from having a higher expected stock of human capital. After this point, the changes in average hourly wages for the agents of the same age in an abstract occupation are defined by changes in the prices of human capital, shocks to human capital in an abstract occupation, and selection into abstract and routine occupations.

Equation 5 expresses these changes for mean log-hourly wages of agents in the model. Shocks to human capital in abstract occupations are i.i.d. and mean-zero and therefore, in the absence of selection to and out of an abstract occupation, changes in wages are driven by the changes in $P_{A,t}$ over time.

$$\begin{gathered} Mean[ln\ h_{A,j+1}] = Mean[ln\ h_{A,j}] \implies \\ Mean[ln\ P_{A,t+1}h_{A,j+1}] - Mean[ln\ P_{A,t}h_{A,j}] = ln\ P_{A,t+1} - ln\ P_{A,t} \end{gathered} \tag{5}$$

Price changes from Equation 3 can be estimated using repeated cross-sectional data. As in Bowlus and Robinson (2012), this paper uses cross-sectional Current Population Survey (CPS) data to obtain price series for abstract labor. Additionally, although in the model human capital in routine occupations $h_{R,j}$ is not subject to agents' decision-making, the same "flat spot" approach is applied to the estimation of price series for routine labor. The reason for this is that the evolution of human capital in a routine occupation independent of the agents' decision making is introduced in the model as a simplification which facilitates the computational process, but which is not likely to hold outside of the model. Similarly to abstract occupations, the change in prices for human capital in routine occupations is defined as:

$$Mean[ln\ P_{R,t+1}h_{R,j+1}] - Mean[ln\ P_{R,t}h_{R,j}] = ln\ P_{R,t+1} - ln\ P_{R,t} \tag{6}$$

The model-based identification strategy expressed in Equations 5 and 6 suggests that the price series can be estimated on cross-sectional CPS data from Equation 8. Here, the changes in prices are calculated as changes in mean hourly wages for synthetic cohorts of workers in abstract and routine occupations. Synthetic cohorts are formed out of workers of age j in year t and workers of age $j+1$ in year $t+1$.

$$\begin{gathered} Mean[ln\ h_{k,j+1}] = Mean[ln\ h_{k,j}] \implies Mean[ln\ P_{k,t+1}h_{k,j+1,t+1}] - Mean[ln\ P_{k,t}h_{k,j,t}] \\ = ln\ P_{k,t+1} - ln\ P_{k,t},\ where\ k \in \{A, R\} \end{gathered} \tag{7}$$

Equation 8 identifies price series for human capital in abstract and routine occupations only in the absence of ability-based selection to and out of these occupations. However, as is evident from Figure 3, mobility with the signs of ability-based selection between routine and abstract occupations persists until the later stages of the working life cycle. For instance, switches out of abstract occupation would be more frequent for agents with the lower stock of human capital and ability. For these agents, shocks to human capital are more likely to decrease their wages up to the level when they will be better-off working in routine occupations. An increase in mean earnings, associated with an increase in mean ability due to selection out of abstract occupations, would then be erroneously attributed to growth in the price of human capital in abstract occupations. On the other hand, a rise in prices for abstract human capital and a fall in prices for routine human capital would make relatively less-able agents from routine occupations enter abstract occupations. This would lead to a fall in mean ability, and human capital, of agents in abstract occupations, masking a rise in prices of human capital in this occupational category. Moreover, in the CPS data there is mobility between the two occupational categories included in the model and the categories of service occupations, unemployment, and non-participation. The ability-based selection into and out of abstract and routine occupations associated with these additional labor force statuses can further bias the estimates.

Given that selection into and out of abstract and routine occupations contributes to a change in mean hourly wages with opposite signs, it is difficult to predict the sign of the resulting bias that it introduces to the price series estimated based on Equation 8. However, it is possible to choose a subset of the population for which mobility into and out of the occupation would be minimized, therefore minimizing the bias arising from it.

4.2 Occupational Mobility Across Educational Groups

To determine the groups with the lowest mobility, I make use of the longitudinal Annual Social and Economic Supplement of CPS data (ASEC CPS), in which individuals are observed for two consecutive years. The four panels of Figure 3 show mobility into and out of abstract and routine occupations for college, some college, and high school workers in their respective flat spot age ranges[5]. The flat spot age ranges are 50-59 for college, 48-57 for some college, and 46-55 for high school, as suggested by Bowlus and Robinson (2012) and

[5] A more model-consistent way of determining the groups with the lowest mobility would be to use workers from different ends of ability distribution. Unfortunately, ability measures are not available for the large-scale datasets including the CPS, and NLSY79 data cannot be used in the "flat spot" approach since it follows only a narrow set of cohorts.

are chosen to minimize the cohort effects on the estimated price series. Using the individual observations in the consecutive years, the share of agents leaving the respective occupation in year t is calculated as the share of all agents reporting that occupation as the primary one in year $t-1$ and switching to another occupation, unemployment or non-participation in year t. The share of agents joining the occupation in year t is calculated as the share of all agents reporting that occupation as the primary one in year t who are observed in a different occupation, unemployment or non-participation in year $t-1$.

The top-left panel of Figure 3 shows that the share of agents leaving abstract occupations in each year is lowest for the college education group, oscillating around 10 per cent annually. The shares of workers with some college and high school education leaving abstract occupations are much higher, more volatile, and possess an apparent upward trend. If workers with some college and high school education are, on average, of lower ability than college workers, the upward trend in the shares of workers leaving abstract occupations can impose an upward bias on the estimates of human capital price in abstract occupations. Over time, this bias may result in a (steeper) upward trend in the estimated prices series. The higher volatility of the shares of some college and high school workers leaving abstract occupations is likely associated with the smaller shares of workers from these education groups working in abstract occupations.

A similar pattern is observed for the shares of workers joining abstract occupations (bottom-left panel of Figure 3). High school and some college workers in their flat spot age ranges join abstract occupations more frequently than workers with college education, and the shares of those joining increase over time. With the average ability of some college and high school workers being lower than for college workers, an increase in the shares of these workers joining abstract occupations potentially biases downwards the estimated price of human capital in abstract occupations.

The top- and bottom-right panels of Figure 3 demonstrate the shares of workers from different educational groups leaving and joining routine occupations. In contrast to abstract occupations, the lowest mobility into and out of routine occupations is observed for high school workers. The highest shares of workers leaving and joining routine occupations are observed for college workers. The shares of college and some college workers moving into and out of routine occupations are more volatile over time than those for high school workers. There are no apparent upward trends into mobility to and out of routine occupations for any educational group that would persist for the whole period under investigation. However, the shares might increase or decrease over shorter periods of time. For instance, for some college workers there is an increase in the share of those joining routine occupations between 1994 and 2006. The share of college workers joining routine occupations tends to decrease on average between 1976 and 2009.

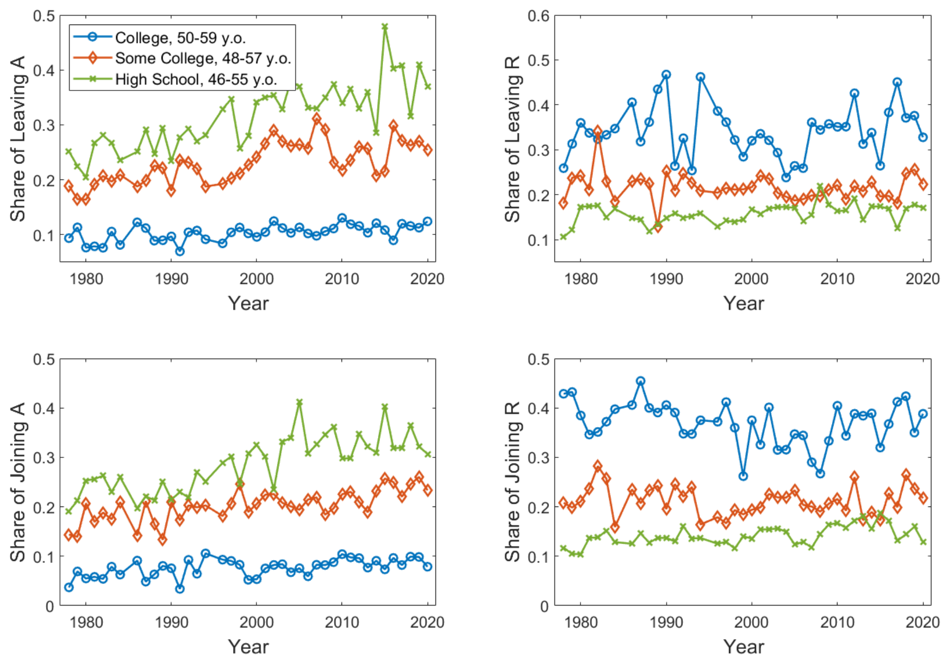

Figure 3: Mobility into and out of Abstract and Routine Occupations by Education Groups
Note: The sample includes all males from the longitudinal ASEC CPS data with valid observations of employment status in years $t-1$ and t whose reported status was: (i) employed ('at work' or 'has job, not at work last week') with valid observations of occupational codes; (ii) unemployed ('unemployed experienced worker' or 'unemployed new worker'); (iii) not in labour force. Educational groups are based on Jaeger (1997): (i) high school – 12 completed years; (ii) some college – 13-15 completed years; (iii) college degree – at least 16 completed years of education.

While all of the changes in the shares of workers leaving and joining abstract and routine occupations cannot be reproduced within the simple partial equilibrium framework used in this paper, the model can be used to rationalize some of the trends and relative frequencies of the mobility in between of the two occupational categories. From the perspective of the model, workers with some college and high school education are characterized by low to medium values of human capital in abstract occupations. In the course of RBTC, as human capital prices in abstract, as well as routine, occupations are changing, larger shares of such workers find themselves better off working in abstract occupations (inequality 2 is satisfied for the larger share of workers), thereby producing an overall upward trend in the shares of some college and high school workers joining abstract occupations. At the same time, as workers with lower ability and human capital in routine occupations switch to abstract occupations, a larger share of them falls back to routine occupations as a result of a negative human capital shock hitting the relatively small human capital stocks of the switchers. In the model, workers with college education correspond to agents with medium to high levels of human capital in abstract occupations. Most of these workers found it optimal to supply abstract labour at the beginning of the period studied. Hence, for them the mobility into and out of the abstract occupations is the lowest of the three education groups.

It must be noted that, in the data, mobility is not limited to switching between the two occupational categories. Some of the workers joining or leaving abstract occupations are leaving to or coming from service occupations, unemployment and non-employment. Similarly, for routine occupations, mobility into and out of the occupational category is closely linked to unemployment, while the model in this paper is only suited for the analysis of the transitions between employment in different occupational categories. Nonetheless, the model can rationalize the highest rate of switching out of routine occupations among workers with high human capital in abstract occupations (college workers in the data). The workers with high human capital receive a negative realization of the idiosyncratic shock in one period, switching to routine occupations, but also have higher chances of returning to abstract occupations in the following periods due to initially higher human capital stock. A high positive correlation between initial human capital in abstract occupations and productivity in routine occupations can also produce the highest share of workers joining routine occupations from college workers.

In addition to the mobility analysis based on Figure 3, I formally test for the presence of differences in time trends in the log hourly wages between workers staying in their respective occupations and those who join or leave them. The analysis is conducted for the "flat spot" age ranges. Tables A.4 and A.5 in the Appendix show the results of the regressions of log hourly wages on the linear time trend, dummy for either joining or leaving an occupation, and interaction term between joining/leaving dummies and time trend. The coefficients on the interaction terms are insignificant for almost all education groups in both abstract and routine occupations, with the only marginally significant coefficient on the interaction term being for high school workers joining abstract occupations. This suggests that the mobility between abstract and routine occupations was not driven by workers with statistically higher or lower wages. From this it follows that the mobility observed is not likely to affect the trend in the price series for human capital in abstract or routine occupations. However, it should be noted that in these regressions, the sample sizes for some college and high school workers in abstract occupations and college and some college workers in routine occupations are at least two times smaller than the samples of college workers in abstract occupations and high school workers in routine occupations. Smaller sample sizes, and higher volatility over time of the shares of workers joining and leaving the two occupations, suggest that the estimates for some college and high school workers in abstract occupations and for college and some college workers in routine occupations can be unreliable.

4.3 Estimated Price Series

Figure 4 demonstrates the price series for human capital in abstract and routine occupations estimated on the cross-sectional CPS data. As suggested by Bowlus and Robinson (2012), to avoid the problem of wage top-coding, means from Equation 8 are replaced with medians. Therefore, the actual equation used to estimate the price series takes the form:

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

The baseline estimates presented here are calculated for the unrestricted sample of males, (who worked at least 25 hours in the previous year) who reported positive earnings. For both occupations in Figure 4, prices are normalized to 1 for 1976. I also estimate the prices using a full time, full year sample (worked at least 1400 hours in the previous year) and the sample with the same restrictions on hours as for the life-cycle moments calculated on NLSY79 data (between 520 and 5820 hours worked in the previous year). The estimated price series based on these alternative samples are available in the Appendix (Figures A.1 and A.2) and are qualitatively and quantitatively similar to the baseline series.

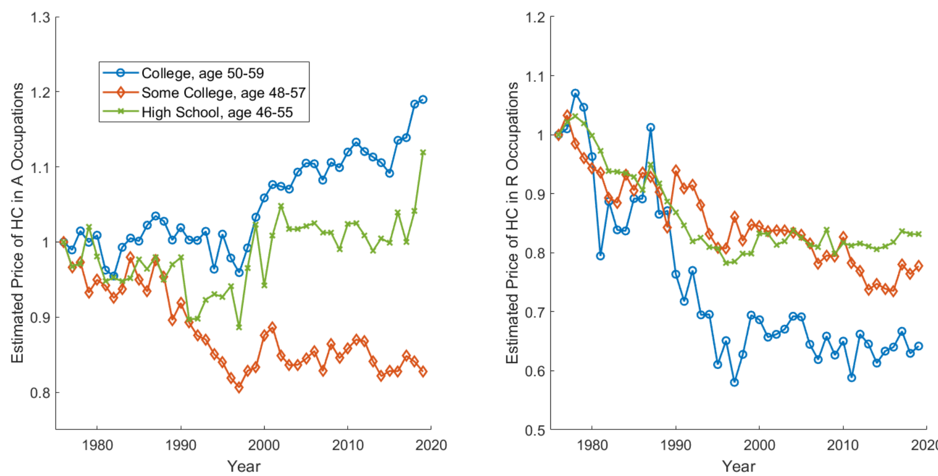

Figure 4: Price Series for Human Capital in Abstract and Routine Occupations

Note: Prices are calculated using cross-sectional CPS data. The sample includes all workers with positive earnings who reported working at least 5 hours a week for at least 5 weeks in the previous year and with valid observations of occupational codes.

Price series for human capital in abstract occupations estimated on the sample of college workers (left panel of Figure 4) suggest that the price for human capital in abstract occupations increased by more than 18 per cent from 1976 to 2019. The growth in human capital prices in abstract occupations was not monotonous: prices rose from 1982 to 1987, then fell until 1997. From 1997, interrupted by short periods of busts, the prices for human capital in abstract occupations were booming, showing a 23 percentage point increase by 2019.

The price series for human capital in abstract occupations estimated on the sample of high school workers show an overall increase of 12 per cent between 1976 and 2019. Human capital prices in abstract occupations, estimated on the sample of some college workers, were non-increasing over most of the period studied. As discussed above, slower growth of human capital price estimates for high school workers and non-increasing prices for some college workers are likely to be associated with the biases caused by high rates of mobility into and out of abstract occupations for these education groups.

The left panel of Figure 4 plots the estimates of prices for human capital in routine occupations. Unlike the estimated price series for abstract occupations, all three series of human capital prices in routine occupations demonstrate a large degree of co-movement: the steepest fall in prices for human capital in abstract occupations occurred between 1978 and 1997, with an overall flattening of the trends at the beginning of the 2000s. For high school workers, by 1997 the prices had decreased to 0.78 per cent of the 1976 price level. After a short period of recovery, between 1998 and 2000, the series shows a virtually flat time trend, with the human capital price in 2019 equal to 83 per cent of that in 1976. Prices estimated on the sample of workers with some college are moving closely with those for high school workers, but also show some steeper fall after 2010. The largest fall in the prices for human capital in routine occupations is observed for college workers – the educational group with the highest and most volatile mobility rates to and from routine occupations.

The estimated price series can be compared with the human capital price series estimated by Bowlus and Robinson (2012). The authors show that, over the same period of time, there is a high degree of comovement between human capital prices across all education categories. Figure 4 shows that, for college and high school workers, there is some comovement within occupational categories. At the same time, conditional on education category, prices for human capital tend to move in the opposite directions for workers employed in routine and abstract occupations. In addition, the degree of comovement between human capital prices, calculated for different education groups within occupational categories, is lower than for the price series using a division based only on the education categories.

Education levels are roughly mapped into skill categories, while division into routine and abstract categories takes into account the task content of occupations. Therefore, the differences between the estimates of Bowlus and Robinson (2012) and those in this paper speak for the relevance of the task-based approach (Acemoglu and Autor, 2011) in the analysis of wage changes happening over recent decades. In the context of the task-based approach, changes in human capital prices in abstract and routine occupations could have contributed to the growing gap between routine and non-routine (abstract and service) wages documented and discussed in the literature (Autor et al., 2008; Autor and Dorn, 2013; Eden and Gaggl, 2018).

Overall, college workers in abstract occupations and high school workers in routine occupations in their "flat spot" age ranges demonstrate the lowest and the least volatile rates of mobility. It is also possible to show that there is no statistically significant difference between the time trend for the workers from these educational groups who join or leave the respective occupations and those who remain in them. This suggests that for college workers in abstract occupations and high school workers in routine occupations the estimated price series of human capital can be considered to be the least biased. In the following sections, I calibrate the working life cycle model described in Section 3 and perform counterfactual exercises using human capital prices in abstract occupations estimated for college workers as $P_{A,t}$ and human capital prices in routine occupations estimated for high school workers as $P_{R,t}$.

5 Calibration and Model Fit

5.1 Calibration

The parameters of the model are calibrated in two stages and consolidated in Table 2. First, the parameters, including discount rate and the prices for human capital in abstract and routine occupations, are set without simulating the model. Discount factor β is set to 0.96, in line with Huggett et al. (2006). The number of lifetime periods (J) equals 41, with agents living from a real age of 18 to 58. Agents in the model are assumed to be aged 18 in 1976. The age premium in routine occupations takes the form $f(j) = \beta_0 + \beta_1 j + \beta_2 j^2$, where coefficients come from the equation $log(y_{j,t}) = \beta_0 + \beta_1 j + \beta_2 j^2 + \gamma_1 t + \gamma_2 t^2 + \epsilon_{j,t}$ estimated on the PSID data with the same sample restrictions as for the NLSY79 data.[6]

Human capital prices follow the second order polynomials fitted to the price series estimated in the previous section. Prices for human capital in abstract occupations are based on the flat spot age range estimates for college workers, while prices for human capital in

[6] In this specification, coefficients β_1 and β_2 capture the age effects and coefficients γ_1 and γ_2 capture the time (year) effects. $\epsilon_{j,t}$ is a zero-mean error term.

routine occupations are based on the estimates obtained for the high school workers. The prices, as well as the fitted second order polynomials used in the model, are plotted in Figure A.3 in the Appendix.

Table 2: Parameters of the Model

Definition	**Symbol**	**Value**	**Source**
Discount factor	β	0.9615	Huggett, Ventura and Yaron (2006)
Length of the life cycle	J	41	N/A
Abstract HC prices	$P_{A,j}$	$[1, 1.18]$	CPS data
Routine HC prices	$P_{R,j}$	$[0.80, 1]$	CPS data
Age premium in routine job	$f(j)$	$f(j) = -1.09 + 0.1523j - 0.0017j^2$	PSID data
HC elasticities	α_1, α_2	0.61, 0.15	Model simulations
Initial conditions	$(h_0, a, \eta) \sim LN(\mu_x, \Sigma)$	$(\mu_h, \mu_a, \mu_\eta) = (4.77, -1.50, 5.23)$; $\begin{bmatrix} \sigma_h^2 & \sigma_{ha} & \sigma_{h\eta} \\ \sigma_{ah} & \sigma_a^2 & \sigma_{a\eta} \\ \sigma_{\eta h} & \sigma_{\eta a} & \sigma_\eta^2 \end{bmatrix} = \begin{bmatrix} 0.62 & 0.19 & 0.33 \\ 0.19 & 0.29 & 0.14 \\ 0.33 & 0.14 & 0.55 \end{bmatrix}$	Model simulations
Abstract HC shocks	$z \sim N(\mu_A, \sigma_A^2)$	$(\mu_A, \sigma_A) = (0, 0.07)$	Model simulations
Routine HC shocks	$z \sim N(\mu_R, \sigma_R^2)$	$(\mu_R, \sigma_R) = (0, 0.09)$	Model simulations
Price ratio in j=1	$\mathrm{P}_{R,1976}/P_{A,1976}$	0.70	Model simulations

Next, the model is simulated to calibrate a vector ψ of 14 values: the parameters of the initial distribution of a, h_0 and η, set to be joint log-normal; abstract human capital function elasticities α_1 and α_2; variances of shocks to human capital in abstract and routine occupations, set to be normally distributed with zero mean; the price ratio $\frac{P_{R,t}}{P_{A,t}}$ in year 1976. The parameters are chosen so that the simulated model is able to reproduce a set of moments from the NLSY79 data. Specifically, the calibration procedure targets the age profiles of the abstract wage premium and the variance of log earnings (from the age of 23 to 57). Figure A.4 in the Appendix shows both estimated profiles. Additionally, routine and abstract occupational distributions by ability quartiles, at the of age 25 (Figure 1), and RA and AR switch probabilities (Figure 2) are used as the targets. The calibration procedure also directly targets the share of routine workers at the age of 25. The parameters in a vector

ψ are chosen to minimize the sum of squared log distances between the moments produced by simulating the model and their counterparts from the NLSY79 data.

5.2 Model Fit

Figure 5 demonstrates the fit of the model to the first set of data moments. The model-based abstract wage premium profile closely follows its data counterpart. The model is able to reproduce not only the the magnitude of the variance of log earnings over the working life cycle of the NLSY79 cohorts, but also the U-shape of the profile. The model-based variance, however, reaches the bottom of the U-shape 3 years later (at the age of 35) than the data-based profile (at the age of 32). There is a trade-off between fitting the variance and occupational mobility profiles: higher mean ability a makes it possible to reproduce the RA switches more closely, while postponing the moment when the earnings of high ability agents overtake the earnings of the low-ability agents – the point where the bottom of the U-shape occurs[7]. There is a close fit of the distribution of workers by ability quartiles in abstract and routine occupations at the age of 25. The model generates ability-based selection into two occupational categories, with the probability of an agent being observed in an abstract (routine) occupation rising (falling) in ability a.

RA and AR mobility produced by the model is compared with RA and AR mobility in the NLSY79 data in Figures 6 and 7. Overall, the model is able to reproduce the RA mobility patterns observed in the data: the probability of an RA switch rises with ability. The probability of an RA switch at the beginning of the working life cycle is also higher than in its later stages. In the model, a fall in RA mobility is observed mostly between the ages of 23-33 and 34-44, while in the data RA mobility also continues to fall between the ages of 34-44 and 45-55. In the later years of the NLSY79 data, as the workers select out of employment, the sample of abstract and routine workers is composed of workers with

[7]The implication of the model is that workers with higher ability tend to spend more time in learning for more years at the beginning of the working life cycle than those with lower ability and therefore spend less time working. For these workers, benefits from the larger stock of human capital at the later stages of the working life cycle offset the earnings forgone from longer years of learning at the beginning of the working life cycle.

higher labor force attachment. In a framework featuring the accumulation of human capital, higher labor force attachment closer to the end of the working life cycle can be rationalised by a higher stock of human capital. Assuming the specificity of human capital across the occupational categories, higher labor force attachment also implies higher attachment to a particular occupational category, therefore producing a further fall in the probability of an RA switch. At the same time, in a simple model with only two occupational categories and without a non-employment option, workers in routine occupations can only choose to switch to an abstract occupation when, for example, their stock of human capital in a routine occupation is hit by a negative shock.

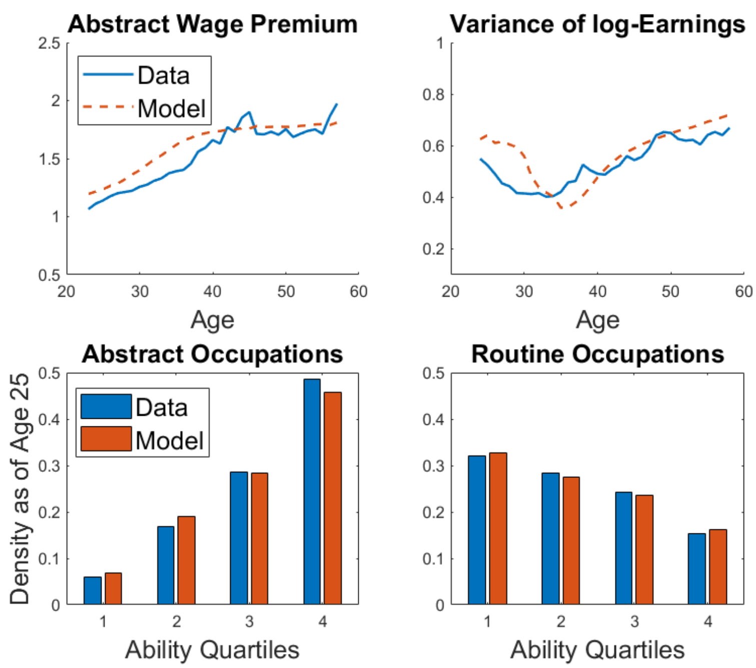

Figure 5: Model Fit: Earnings Statistics and Ability Distributions

Note: Data-based abstract wage premium and variance profiles are calculated as the age effects from the regressions of the respective data moments for each age-cohort cell on age and cohort dummies. Distributions in abstract and routine occupations are calculated at age 25.

Figure 7 also shows the AR mobility produced by the calibrated model. The model-based probabilities of an AR switch exhibit an ability-based selection qualitatively and quantitatively similar to that observed in the data. Across all ability quartiles the probabilities of an AR switch are falling over the working life cycle. In the model developed in this study, AR switches are predominantly due to negative realizations of shocks to human capital in abstract occupations and positive realizations of shocks to human capital in routine occupations. Ability-based selection is achieved via a strong positive correlation between a and $h_{A,0}$.

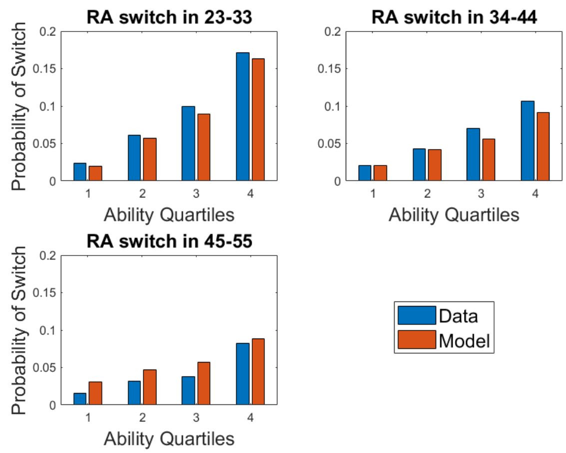

Figure 6: RA Mobility in the Data vs. Mobility in the Model

Note: Both in the data and in the model, for each period all agents in the occupational category are arranged into ability quartiles. In the data, the probabilities of a switch are calculated as the share of individuals aged j in year t from ability quartile q who in period $t+2$ are observed in a broad occupational category different from that in which they were observed in year t. In the model, the probabilities of a switch are calculated as the share of individuals of age j in ability quartile q changing their occupation by age $j+2$.

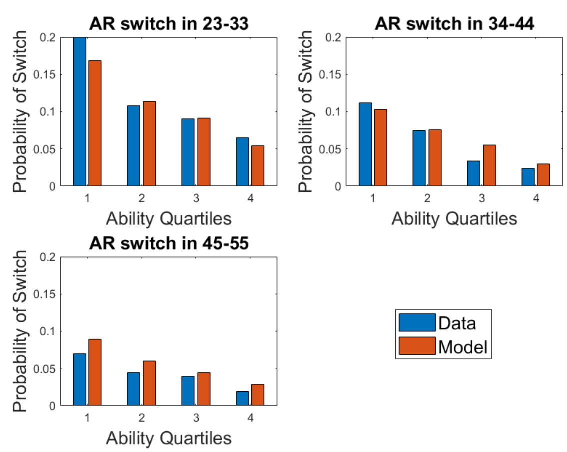

Figure 7: AR Mobility in the Data vs. Mobility in the Model

Note: Construction of probabilities is the same as for Figure 6.

6 Implications of the Model

6.1 Non-Targeted Moments

The calibration procedure described in the previous section directly targets only the share of routine workers at the beginning of the working life cycle, at the age of 23. Figure 8 shows how the share of routine workers in the model evolves over the whole working life cycle and compares it to the shares of routine workers in the NLSY79 data. The model closely reproduces a steep fall in the share of routine workers for the first years of the working life cycle. For the later ages, a fall in the share of routine workers implied by the model is less steep than its data counterpart. Overall, the model is able to reproduce 81 per cent of a fall in the share of routine workers between ages 23 and 54. This fall is generated by a share of routine workers who accumulate human capital to join abstract occupations later on, as well as by a simultaneous increase in the price for human capital in abstract occupations and a fall in the price for human capital in routine occupations which directly affect the Inequality in 2.

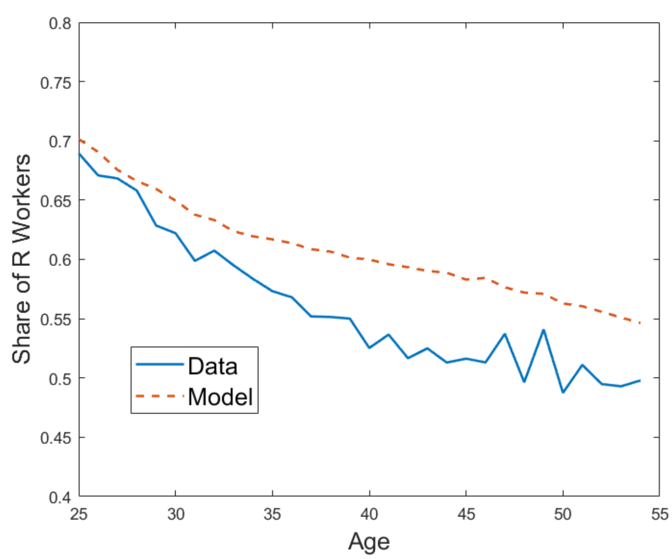

Figure 8: Share of Routine Workers over the Working Life Cycle

Note: The data counterpart is calculated as the share of routine workers in the sample of males, consisting of routine and abstract workers.

As discussed in Section 2.2, the initial distribution by ability quartiles in abstract occupations shows steeper ability-based selection than the final distribution (Figure 1). Ability-based selection into routine occupations is less strong at the beginning of the working life cycle than at the end. The calibrated model reproduces these changes in selection. As is evident from Figure 9, the proportion of high-ability agents in abstract occupations is higher at the age of 25 than at the age of 50. At the same time, the share of low-ability agents in routine occupations rises by the age of 50. The net outflow of workers from routine occupations produced by the model implies that some workers with medium to low ability are switching to abstract occupation over the working life cycle, therefore dampening the selection in this occupational category. In contrast, as the probability of an RA switch is rising in ability, the share of the least able agents in routine occupations increases.

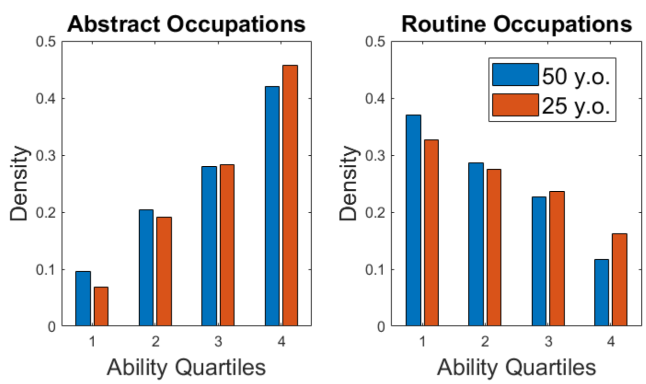

Figure 9: Occupational Distributions by Ability Quartiles in the Model

Note: This figure shows the share of workers in abstract and routine occupations by the quartiles of initial condition a in the calibrated model.

Figure A.5 in the appendix compares the shapes of the mean earnings profiles in the NLSY79 data with those from the simulations of the calibrated model. Mean earnings increase steeply over the lifetime of the NLSY79 cohorts[8]. The calibrated model, which directly fits the abstract wage premium, closely reproduces the shape of the data-based mean earnings profile.

[8]The estimated age effects are much larger than those estimated on other panel data, e.g., PSID, but are in line with the mean-earnings profiles calculated in Cunha and Heckman (2007)

6.2 The Effect of Changes in Human Capital Prices

To see the effect of a change in human capital prices, I conduct a counterfactual exercise in which the prices for human capital in both occupational categories are kept at their 1979 levels. The rest of the parameters are set to be the same as for the calibrated full model with changing human capital prices. Figure 10 contrasts the resulting counterfactual simulated moments with the baseline simulations of the model where prices for human capital change as in the data. For the first 10 years of the working life cycle, the counterfactual abstract wage premium (left panel of Figure 10) closely follows the abstract wage premium profile produced by the full model. The reason for this is that at the beginning of the working life cycle, even with no change in the prices of human capital, workers dedicate most of their time to the accumulation of human capital and, when there is a change in the prices, they cannot increase their time investment into human capital accumulation due to the time constraint. Moreover, in the 1980s, when the NLSY79 cohorts were at the beginning of their working life cycle, the prices for human capital in abstract occupations did not show much growth, and the fall in the prices for human capital in routine occupations was gradual and were not reflected in the premium right away.

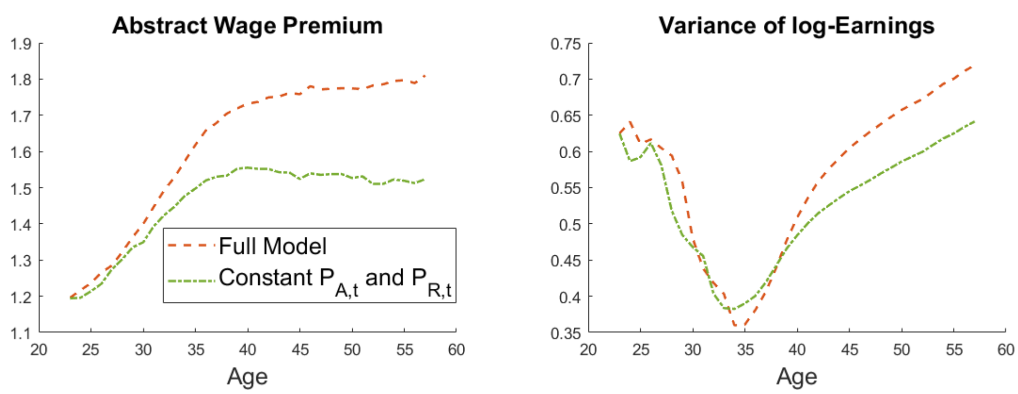

Figure 10: Earnings Statistics: Full Model vs. Constant Human Capital Prices

After the age of 30-33, the divergence between the profiles of the abstract wage premium becomes more apparent. For the model with changing human capital prices, a period of steep growth in the abstract wage premium, associated with the active accumulation of human capital in abstract occupations, continues almost up to the age of 40, while the abstract wage premium profile in the model with fixed human capital prices starts to flatten around the age of 35. After the age of 40, the abstract wage premium in the full model continues to rise slowly, mostly due to the growth in the price of human capital in abstract occupations. The abstract wage premium under the counterfactual scenario of no change in prices shows a mild downward trend – due to the agents with on average lower human capital switching from routine to abstract occupations. By the age of 57, the change in human capital prices contributes to an increase in the abstract wage premium of 28.6 per cent.

Table 3: 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	0.38	0.54	0.62
	(0.92)	(1.06)	(0.91)	(0.89)
No shocks	0.54	0.19	0.46	0.54
	(0.85)	(0.53)	(0.79)	(0.78)
No variation in initial conditions	0.09	0.09	0.13	0.18
	(0.14)	(0.24)	(0.2)	(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.

The right-side panel of Figure 10 compares the evolution of variance of log-earning in the full model and in the counterfactual with the fixed human capital prices. Most of the rise in variance due to the changing prices takes place in the second half of the working life cycle. By the end of the working life cycle, the growing gap between prices for human capital in abstract and routine occupations accounts for up to 10.8 per cent of the variance. Additionally, more active accumulation of human capital under changing prices leads to the

U-shape of the profile reaching its minimum at the lower level of variance and appearing by two years later as compared to the case with the fixed prices.

Compared to other sources of earnings variation in the model, changing prices appear to have a rather modest effect on the variance of log-earnings. Table 3 shows the variances of log-earnings at different ages produced by the models, from which one out of three sources of variation in earnings is removed. The most important source of variation in earnings is the variation in initial conditions: the model with all agents having the same mean realization of the three initial conditions $a, h_{A,0},$ and η is able to reproduce only up to 26 per cent of the variance of the full model where initial conditions have a calibrated dispersion. The other important source of variation in earnings are the shocks to human capital in abstract and routine occupations. Around the age of 35, the model without these shocks is only able to produce just above half of the variance observed in the full model. At the same time, the model with constant human capital prices is able to produce around 90 per cent of the variance produced by the full model, with the variance around the age of 35 reaching its minimum at a slightly higher level due to the less intense accumulation of human capital under no growth in prices.

6.3 Human Capital Responses

A simultaneous rise in the price of human capital in abstract occupations and a fall in price of human capital in routine occupations creates incentives for workers to accumulate more human capital in abstract occupations and to switch from routine to abstract occupations. The fact that agents respond to the changes in prices by altering their human capital decisions and occupational choices can either amplify or mitigate the effect of a price change.

To isolate the contribution of human capital responses, I run a counterfactual exercise in which the agents in the model with human capital prices evolving as estimated from the data do not respond to the price changes and keep following the policies optimal under the constant human capital prices. Figure 11 shows the results of such a counterfactual exercise for the abstract wage premium. Driven solely by price changes, the abstract wage premium under no human capital responses is significantly higher than the wage premiums calculated for the full model and for the model with fixed human capital prices. The fact that the abstract wage premium is higher under no human capital responses than in the full model, where agents are allowed to adjust their decisions to the changing prices, suggests that human capital responses serve to dampen a rise in the premium.

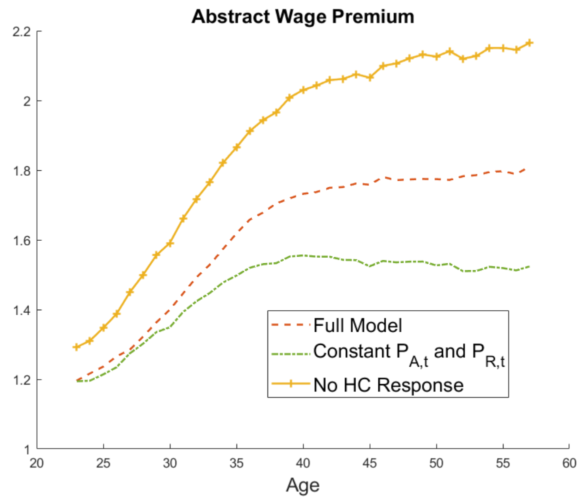

Figure 11: Human Capital Response and Abstract Wage Premium

Note: The abstract wage premium profile for the no HC response counterfactual is calculated from the simulations of the model with human capital prices changing as estimated from the data, with the agents following policies optimal for the case when $P_{A,t}$ and $P_{R,t}$ are constant. The rest of the parameters for the no HC response counterfactual are as in the full model.

Figure 12 shows a higher proportion of workers staying in routine occupations under no changes in prices. Most of the decline in the share of routine workers over the working life cycle is associated with the price changes and the resulting human capital responses. Figure 13 further compares the probabilities of RA switches under changing and constant human capital prices across ability quartiles. The figure suggests that the estimated changes in human capital prices lead to an increase in the RA mobility across all ability quartiles. Figure A.6 in the Appendix, which breaks down the human capital responses by ability quartiles, suggests that an increase in the RA mobility is actually associated with a more intensive accumulation of human capital in abstract occupations across all ability quartiles.

Given a strong positive correlation between the initial human capital and ability implied by the calibration procedure, workers from lower ability quartiles also have lower stocks of human capital at the moment they join abstract occupations. A large inflow of workers with lower ability and human capital into abstract occupations puts a downward pressure on the average wages in these occupations, compensating for a rise in wages for highly-able workers employed in abstract occupations. More intensive accumulation of human capital across all ability quartiles in response to a change in its prices results in the abstract wage premium being 35.5 percentage points lower than it would be in the absence of human capital responses.

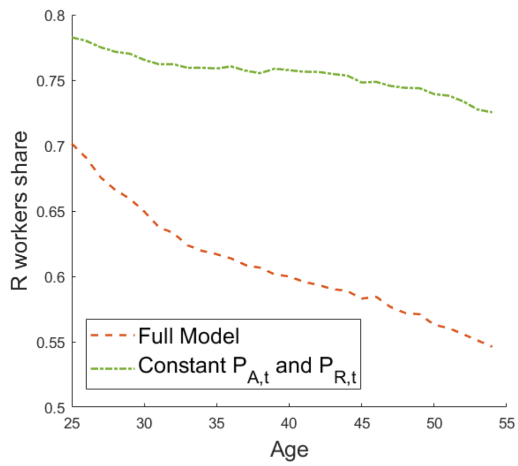

Figure 12: Share of Routine Workers: Changing vs. Constant Human Capital Prices

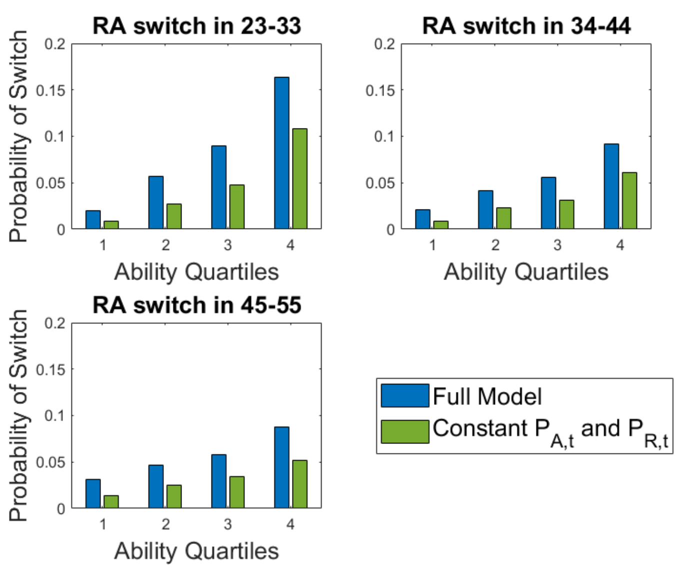

Figure 13: Probability of RA Switch: Changing vs. Constant Human Capital Prices

7 Conclusion

In this study, I investigate the effect of routine-biased technological change, and the associated changes in prices for human capital in abstract and routine occupations, on earnings inequality over the working life cycle for agents with different learning ability and initial human capital. I conduct the analysis on the NLSY79 data. The data reveals the presence of ability-based sorting in routine and abstract occupations, which persists over the working life cycle. Over the working life cycle there is a large net outflow of workers from routine to abstract occupations. The probability of switching from routine to abstract occupation increases in ability.

I further develop and calibrate the life-cycle model of human capital accumulation with occupational choice and calibrate it to the NLSY79 data. To introduce the effect of RBTC into the model, I estimate the price series for human capital in abstract and routine occupations on the cross-sectional CPS data using the flat spot approach. The estimated price series reveals a significant fall in prices for human capital in routine occupations and an increase in prices for human capital in abstract occupations.

Counterfactual exercises conducted on the calibrated model suggest a modest contribution of RBTC to the variance of log-earnings, with the most variation in earnings coming from variation in the initial conditions. There is a significant contribution of RBTC to the growth of the abstract wage premium over the working life cycle. However, individual responses to RBTC dampen the growth in the abstract wage premium. An increase in mobility from routine to abstract occupations across agents with different abilities and stocks of human capital results in a fall of the average wage in abstract occupations.

References

Acemoglu, D. and D. Autor (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In *Handbook of Labor Economics*, Volume 4, pp. 1043–1171. Elsevier.

Acemoglu, D. and P. Restrepo (2018a). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review 108*(6), 1488–1542.

Acemoglu, D. and P. Restrepo (2018b). Robots and Jobs: Evidence from US Labor Markets. *MIT Working Paper Series*.

Autor, D. and D. Dorn (2009). This Job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure. *American Economic Review 99*(2), 45–51.

Autor, D. H. and D. Dorn (2013). The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review 103*(5), 1553–1597.

Autor, D. H., D. Dorn, and G. H. Hanson (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review 103*(6), 2121–2168.

Autor, D. H., L. F. Katz, and M. S. Kearney (2006). The Polarization of the U.S. Labor Market. *AEA Papers and Proceedings 96*(2), 189–194.

Autor, D. H., L. F. Katz, and M. S. Kearney (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics 90*(2), 300–323.

Autor, D. H., F. Levy, and R. J. Murnane (2003). The skill content of recent technological change: an empirical exploration. *Quarterly Journal of Economics*, 55.

Ben-Porath, Y. (1967). The Production of Human Capital and the Life Cycle of Earnings. *Journal of Political Economy 75*(4, Part 1), 352–365.

Bowlus, A. J. and C. Robinson (2012). Human Capital Prices, Productivity, and Growth. *American Economic Review 102*(7), 3483–3515.

Cavounidis, C. and K. Lang (2020). Ben-Porath Meets Lazear: Microfoundations for Dynamic Skill Formation. *Journal of Political Economy 128*(4), 1405–1435.

Cortes, G. M. (2016). Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data. *Journal of Labor Economics 34*(1), 63–105.

Cortes, G. M., N. Jaimovich, and H. E. Siu (2017). Disappearing routine jobs: Who, how, and why? *Journal of Monetary Economics 91*, 69–87.

Cunha, F. and J. J. Heckman (2007). The Evolution of Inequality, Heterogeneity and Uncertainty in Labor Earnings in the U.S. Economy. *NBER Working Paper Series*.

Donovan, K. and C. Herrington (2019). Factors affecting college attainment and student ability in the U.S. since 1900. *Review of Economic Dynamics 31*, 224–244.

Eden, M. and P. Gaggl (2018). On the welfare implications of automation. *Review of Economic Dynamics 29*, 15–43.

Firpo, S., N. M. Fortin, and T. Lemieux (2011). Occupational Tasks and Changes in the Wage Structure. *SSRN Electronic Journal*.

Frey, C. B. and M. A. Osborne (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change 114*, 254–280.

Goos, M. and A. Manning (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *Review of Economics and Statistics 89*(1), 118–133.

Heckman, J. J., L. Lochner, and C. Taber (1998). Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of Labor Earnings with Heterogeneous Agents. *Review of Economic Dynamics*.

Hendricks, L. and T. Schoellman (2014). Student abilities during the expansion of US education. *Journal of Monetary Economics 63*, 19–36.

Huggett, M., G. Ventura, and A. Yaron (2006). Human capital and earnings distribution dynamics. *Journal of Monetary Economics 53*(2), 265–290.

Huggett, M., G. Ventura, and A. Yaron (2011). Sources of Lifetime Inequality. *American Economic Review 101*(7), 2923–2954.

Jaeger, David, A. (1997). Reconciling the Old and New Census Bureau Education Questions: Recommendations for Researchers. *Journal of Business and Economic Statistics*, 300–309.

Jaimovich, N. and H. E. Siu (2014). The Trend is the Cycle: Job Polarization and Jobless Recoveries. *Manuscript*.

Kong, Y.-C., B. Ravikumar, and G. Vandenbroucke (2018). Explaining cross-cohort differences in life-cycle earnings. *European Economic Review 107*, 157–184.

Krusell, P., L. E. Ohanian, J.-V. Rios-Rull, and G. L. Violante (2000). Capital-skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica 68*(5), 1029–1053.

Michaels, G., A. Natraj, and J. Van Reenen (2014). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. *The Review of Economics and Statistics 96*(1), 60–77.

Nordhaus, W. D. (2007). Two Centuries of Productivity Growth in Computing. *The Journal of Economic History 67*(1), 128–159.

PricewaterhouseCoopers (2018). Will robots really steal our jobs?

Roy, A. D. (1951). Some Thoughts on the Distribution of Earnings. *Oxford Economic Papers, New Series 3*(2), 135–146.

Sachs, J., S. Benzell, and G. LaGarda (2015). Robots: Curse or Blessing? A Basic Framework. Technical Report w21091, National Bureau of Economic Research, Cambridge, MA.

Sachs, J. and L. Kotlikoff (2012). Smart Machines and Long-Term Misery. Technical Report w18629, National Bureau of Economic Research, Cambridge, MA.

A Appendix

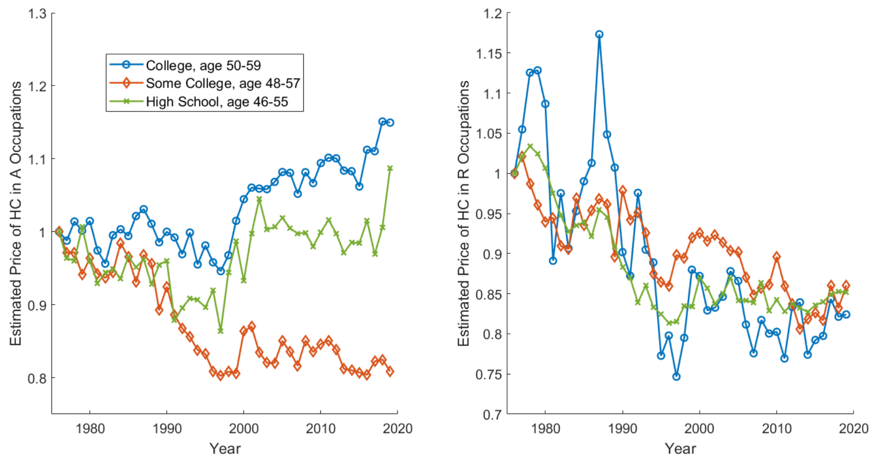

Figure A.1: Price Series for Human Capital in Abstract and Routine Occupations: Full-Time, Full Year Sample

Note: Prices are calculated using cross-sectional CPS data. The sample includes all workers with positive earnings who reported working at least 35 hours a week for at least 40 weeks last year and with valid observations of occupational codes.

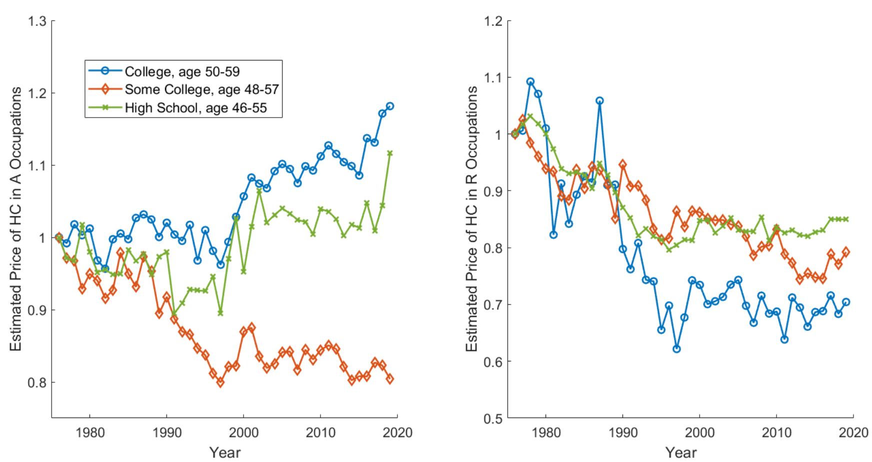

Figure A.2: Price Series for Human Capital in Abstract and Routine Occupations: NSLY79 Hours Sample

Note: Prices are calculated using cross-sectional CPS data. The sample includes all workers with positive earnings who reported working between 520 and 5820 hours last year and with valid observations of occupational codes.

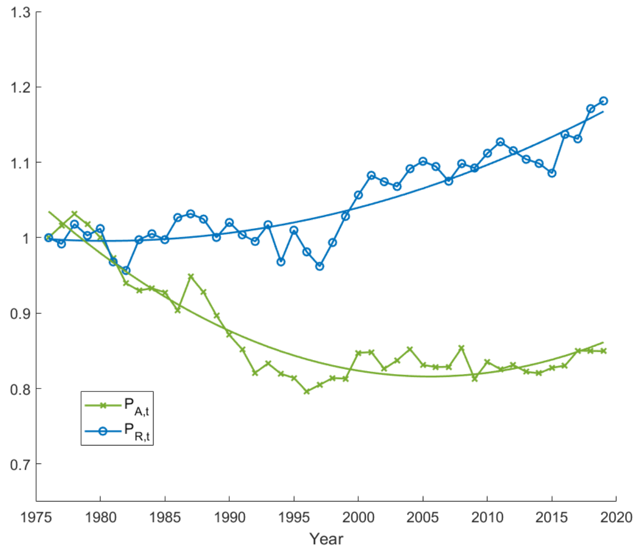

Figure A.3: Price Series for Human Capital Used in the Model

Note: $P_{A,t}$ is estimated for the flat spot age range of college workers; $P_{A,t}$ is estimated for the flat spot age range of high school workers. The model is simulated using the the second degree polynomials fitted to the actual price series.

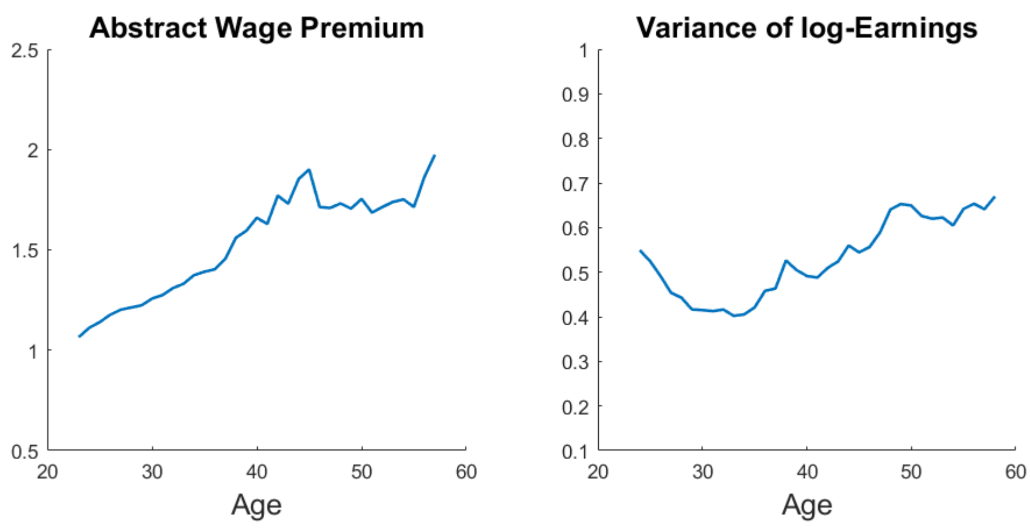

Figure A.4: Earnings Statistics for the NLSY79 Data

Note: The abstract wage premium profile is calculated as age effects $\beta_j^{prem} + \mu^{prem}$ from a regression of the abstract premium on the full set of age and cohort dummies: $Premium_{j,c} = \mu^{prem} + \alpha_c^{prem} + \beta_j^{prem} + \epsilon_{j,c}^{prem}$. Variance of log-earnings profile is calculated as age effects $\beta_j^{var} + \mu^{var}$ from a regression of variance of log-earnings on the full set of age and cohort dummies: $Var_{j,c} = \mu^{Var} + \alpha_c^{Var} + \beta_j^{Var} + \epsilon_{j,c}^{Var}$.

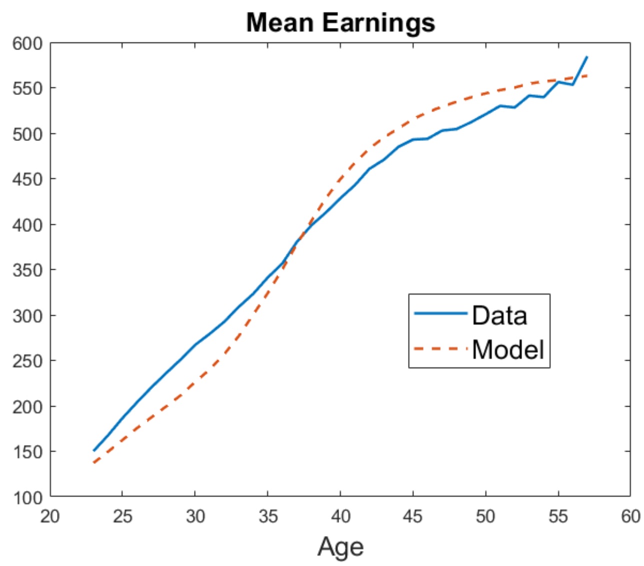

Figure A.5: Mean Earnings Profile: Data vs. Model

Note: The data-based mean earnings profile is calculated as the age effects $exp(\beta_j^e)$ from a regression of log mean real earnings $ln(e_{j,c})$ on the full set of age and cohort dummies: $ln(e_{j,c}) = \mu^e + \alpha_c^e + \beta_j^e + \epsilon_{j,c}^e$. For both the model- and data-based profiles, mean earnings at the age of 21 are normalized to 1.

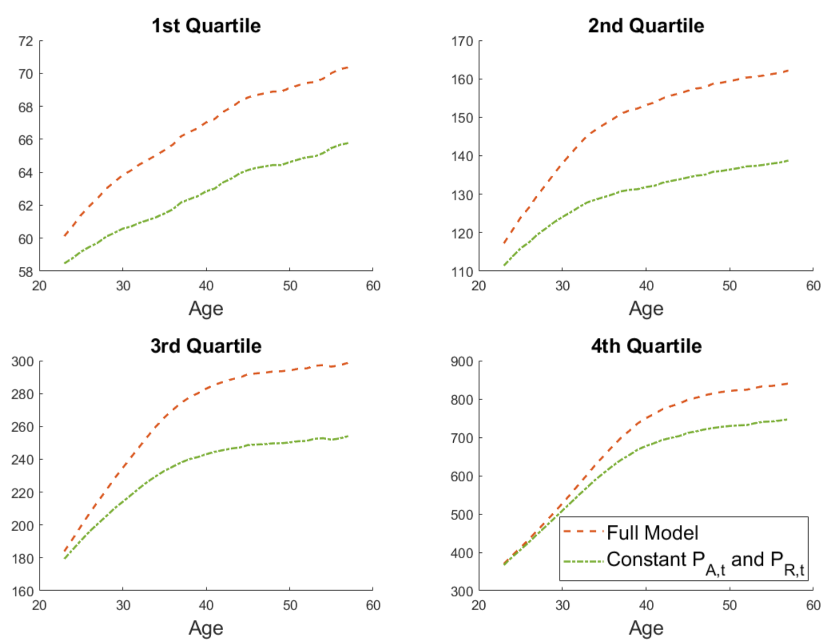

Figure A.6: Human Capital Responses by Ability Quartiles

Table A.1: NLSY79 Sample of Males by Age and Occupational Categories

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	0.27	0.34	0.38	0.41	0.42	0.43	0.45	0.37
Routine	0.63	0.58	0.54	0.50	0.48	0.47	0.46	0.54
Service	0.10	0.08	0.08	0.09	0.10	0.10	0.09	0.09

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 of at least $1500 for those above 30 y.o. (earnings are in 1979 dollars). Such a restricted sample of males consists of 3,003 individual observations.

Table A.2: Occupational Paths for Abstract Workers (by ability quartiles)

Occupation in period:			**Fraction of workers(%):**			
(t)	**(t+2)**	**(t+10)**	**Q1**	**Q2**	**Q3**	**Q4**
A	R	R	12.1	8.6	5.6	2.6
A	A	R	10.4	12.4	10.9	4.8
A	A	A	59.6	69.0	75.0	87.9
A	R	A	6.1	4.1	4.1	3.2
A	S	S	2.1	2.1	1.0	0.2
A	S	A	1.1	0.7	0.6	0.6
A	S	R	1.8	0.6	0.5	0.1
A	R	S	1.4	0.3	0.2	0.1
A	A	S	5.4	2.1	2.1	0.6

Note: R-routine occupation, A-abstract occupation, S-service occupation. The first three columns show the periods in which observations of occupational category are taken for each individual: in a current year, in two years and in 10 years. The last four columns show the fractions of workers from different ability quartiles following a particular occupational path. Probabilities of the occupational paths are calculated in the same manner as the switch probabilities for Figure 2. Here, the observations in service occupations are also included.

Table A.3: Labor Income across Different Occupational Paths

	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
***Panel 2:* Abstract Occupations**				
Occ. downgrading (AAR and ARR) vs. staying (AAA)				
Occ.	-0.327***	-0.267***	-0.285***	-0.475***
downgrading	(0.116)	(0.064)	(0.045)	(0.050)
Age	-0.055	0.086***	0.026	0.043***
	(0.097)	(0.026)	(0.017)	(0.014)
Age^2	0.001	-0.001***	-0.000	-0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Year	-0.004	0.020**	0.012*	0.024***
	(0.023)	(0.008)	(0.007)	(0.004)
Nonwhite	-0.047	-0.021	0.061***	-0.039
	(0.043)	(0.033)	(0.019)	(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. The Occ. upgrading dummy is defined as equal to 1 if an individual follows an RRA or RAA (upgrading) occupational path in t, t+2, and t+10, respectively and as equal to 0 if an individual follows an RRR (staying) path; Occ. downgrading dummy is defined as equal to 1 if an individual follows an AAR or ARR (downgrading) occupational path in t, t+2, and t+10, respectively and as equal to 0 if individual follows an AAA (staying) path. Robust s.e. in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A.4: Time Trends in Log Hourly Wages in Abstract Occupations

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 × 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 × 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

Note: Regressions are estimated on the longitudinal ASEC CPS data for the educational groups in their respective flat spot age ranges. 'Joining A' is a dummy variable equal to 1 if an individual was observed in either a service or routine occupation or non-employment in year $t-1$ and was observed in an abstract occupation in year t, and equal to 0 if observed in an abstract occupation in both years. 'Leaving A' is a dummy variable equal to 1 if an individual was observed in an abstract occupation in year t and was observed in either a service or routine occupation or non-employment in year $t-1$, and equal to 0 if observed in an abstract occupation in both years. For joining, the sample includes all males with: (i) valid observations of yearly working hours, pre-tax wage and salary income and occupational codes for the first year out of two adjacent years of observation; and (ii) valid occupational observations reported for the year preceding the first year out of two adjacent years of observation. For leaving, the sample includes all males with: (i) valid observations of yearly working hours, pre-tax wage and salary income and occupational codes for the year preceding the first year out of two adjacent years of observation; and (ii) valid occupational observations reported for the first year out of two adjacent years of observation.

Robust s.e. in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table A.5: Time Trends in Log Hourly Wages in Routine Occupations

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 × 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 × 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

Note: Regressions are estimated on the longitudinal ASEC CPS data for the educational groups in their respective flat spot age ranges. 'Joining R' is a dummy variable equal to 1 if an individual was observed in either an abstract or service occupation or non-employment in year $t-1$ and was observed in a routine occupation in year t, and equal to 0 if observed in a routine occupation in both years. 'Leaving R' is a dummy variable equal to 1 if an individual was observed in a routine occupation in year t and was observed in either a service or abstract occupation or non-employment in year $t-1$, and equal to 0 if observed in a routine occupation in both years. Samples for joining and leaving are constructed the same way as for Table A.4.

Robust s.e. in parentheses, $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Abstrakt

Testuji, jakou měrou přispívají změny individuálního lidského kapitálu k nerovnostem příjmů, které vznikají v důsledku technologických změn v řešení rutinních úloh (RBTC z anglického routine-biased technological change). Vytvářím model životního cyklu s lidským kapitálem a volbou povolaní. Model kalibruji s využitím NSLY79 dat a cen lidského kapitálu pro abstraktní a rutinní povolání. Ceny lidského kapitálu jsou odhadnuty z průřezových CPS dat s využitím „flat spot" přístupu. Dále používám model ke kvantifikaci vlivu rozdílných cen lidského kapitálu na nerovnost příjmů. Zjišťuji, že zvýšení ceny lidského kapitálu v abstraktních povoláních a pokles ceny v rutinních povoláních spojených s RBTC má mírný vliv na vývoj rozptylu logaritmu příjmů – až 10,8 % do konce životního pracovního cyklu. Nicméně, příspěvek RBTC ke zvýšení mezd v abstraktních povoláních v průběhu života kohort NLSY79 je až 28,6 %. Růst vyšších mezd v abstraktních oborech je výrazně limitován reakcí lidského kapitálu pracovníků, kteří přecházejí z rutinních povolání k abstraktnějším povoláním.

Klíčová slova: RBTC, lidský kapitál, modelování životního cyklu, NLSY79, AFQT

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