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Disappearing Stepping Stones: Technological Change and Career Paths*

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Abstract

Which career paths lead workers towards high-skilled non-routine cognitive occupations? Using PSID data, we show that, for a significant share of workers, a career path towards non-routine cognitive occupations goes through middle-skilled routine occupations, with the majority going through a subset of routine cognitive occupations. We then argue that the decline in employment in routine cognitive occupations due to routine-biased technological change can negatively affect the chances of younger cohorts joining high-skilled occupations. To test this hypothesis, we develop a structural occupational choice model that endogenously generates realistic career paths and estimate it using PSID data and job ad data from three major US outlets covering the period from 1940 to 2000. Our estimations suggest that, on average, 6% of workers ending up in non-routine cognitive occupations use routine cognitive occupations as stepping stones that allow them to maintain and accumulate human capital and experience relevant for later employment in high-skilled occupations. A fall in employment opportunities in routine cognitive occupations over the period of the most intensive routine-biased technological change led to at least 1.37 million lost high-skilled workers who got stuck in less skilled occupations.

JEL classification: J24, O33, E24

Key words: routine-biased tech. change, occupational choice, human capital, career paths

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1 Introduction

In the last two decades, there has been a rapid development of the literature dedicated to the effects of routine-biased technological change (RBTC) and automation on the labor market (Autor, Levy, and Murnane, 2003; Autor, Katz, and Kearney, 2006; Acemoglu and Autor, 2011; Autor and Dorn, 2013). Currently, there is a wide consensus that RBTC is the underlying force behind massive reallocation of labor from routine occupations — associated with a specific set of repetitive and well-defined routine tasks that are subject to automation — to non-routine occupations, observed since at least the second half of the 1980s (Acemoglu and Autor, 2011). This reallocation has been studied along several dimensions. Cortes, Jaimovich, and Siu (2017), using CPS data, show that groups of workers who were primarily observed in routine occupations 35-40 years ago are now considerably more likely to be observed in non-routine manual (low-skilled) occupations and in non-employment. Further, Jaimovich et al. (2020) demonstrate that workers with *routine characteristics* are more often observed in the labor market status associated with lower income, i.e., in non-participation or in low-skilled non-routine manual (NRM) occupations. Cortes (2016) argues, based on the PSID data, that the direction of the transition out of routine occupations is ability-dependent, with more able agents having higher chances of joining high-skilled non-routine cognitive (NRC) occupations. Furthermore, younger and more educated workers are more likely to relocate from routine occupations to non-routine cognitive occupations (Autor and Dorn, 2009).

In this paper, we aim to analyze yet another dimension of the observed reallocation of the labor force from middle-skilled occupations. We argue that, besides workers' characteristics, such as ability, education and age, there are factors associated with employment opportunities and career paths that also shape the relocation of labor under the impact of RBTC. We argue that the career paths towards high-skilled (NRC) occupations go through middle-skilled routine cognitive (RC) occupations. Young workers may not be able to join NRC occupations right away due to lack of experience and human capital, as well as due to lower employment opportunities in NRC occupations at the moment of labor market entry. Instead, they first join routine cognitive occupations, where they can maintain and accumulate human capital, and potentially switch to NRC occupations as they become older. Therefore, the reduction of employment opportunities in routine cognitive occupations due to RBTC can negatively affect young workers' chances of following the stepping stone career path from middle-skilled, routine cognitive, to high-skilled, non-routine cognitive, occupations. At the same time, both the lower chances of entering the NRC occupations and the lower employment opportunities in RC occupations may contribute to an increase in the share of workers employed in low-skilled (NRM) occupations. The effect of RBTC on the RC-to-NRC career path can be therefore represented as a *bottleneck*: the workers who do not start their career in NRC occupations right away have lower chances of progressing towards those occupations over the life cycle due to shrinkage in RC employment opportunities and, subsequently, they congregate in NRM occupations and non-employment.

Our study investigates labor reallocation and the *bottleneck effect* due to RBTC in two dimensions. We start from combining Panel Study of Income Dynamics (PSID) data, which covers employment histories of individual workers in the US, with newly available data on job ads (Atalay et al., 2020) to show (i) the presence of the RC-to-NRC career paths throughout the life cycle of workers, and (ii) its relevance to the reallocation of the labor force under the RBTC.

Further, we assess the bottleneck effect using a structural model featuring Roy-type self-selection into one of four major occupations, characterized by different skill prices and different skill productivity: non-routine cognitive (NRC), routine cognitive (RC), routine manual (RM), and non-routine manual (NRM). Individuals are granted with initial skills that are further accumulated on the job through learning-by-doing. Individuals choose occupations based on their comparative advantage to work in those occupations. To simulate changing employment opportunities, the model assumes that the sets of available occupations observed by each individual are drawn randomly from a set of distributions that change over time. Such a model allows us to generate endogenously the RC-to-NRC career paths and to explore the implications of declining employment opportunities in routine jobs, including the bottleneck effect. We estimate the model using the PSID and job ads data and run a set of counterfactual exercises to quantify the contribution of the bottleneck effect to the probability of employment in NRC occupations in later periods of workers lifetime, as well as to establish the role of the associated stepping-stone mechanism.

Our estimations suggest that, on average, 6% of workers ending in NRC occupations use RC occupations as a stepping stone. At the same time, a decrease in employment opportunities in routine cognitive occupations over the period of the most intensive routine-biased technological change led to a loss of more than 1.37 million NRC workers who got stuck in lower skilled occupations and in non-employment. A significant share of workers, however, were able to avoid the bottleneck, reaching NRC occupations through RM and NRM occupations. The depreciation of human capital associated with following these alternative career paths results in the wage loss once workers reach

NRC occupations. The wage loss associated with lower human capital is the most pronounced in the middle of the NRC wage distribution.

The rest of the paper is organized as follows. In Section 2, we describe the relevant literature. In section 3, we perform an empirical assessment of the bottleneck effect as an implication of the change in employment opportunities due to RBTC. Section 4 builds the structural model, which is further parameterized and estimated in Section 5. Finally, Section 6 discusses the fit of the model and its estimated parameters, and runs a set of counterfactual exercises to quantify the bottleneck effect. Section 7 concludes.

2 Related Literature

Our research corresponds to a large family of economics literature that studies the implications of routine-biased technological change on different aspects of labor markets, such as income inequality, employment polarization, and labor reallocation. In particular, studies by Autor, Levy, and Murnane (2003), Autor, Katz, and Kearney (2006), Goos and Manning (2007), and Acemoglu and Autor (2011) build theoretical and empirical foundations of the routine-biased technological change theory and link the automation of tasks through computerization and robotization to job polarization. Clearly, as occupations are different in their task content, some of them are more prone to the automation, implying a decline in employment opportunities in these occupations (Autor, 2010). We contribute into that strand of literature by investigating the consequences of a decline in middle-skill employment opportunities due to polarization for individual career development.

A particular focus of our paper is on the change in occupational career paths under RBTC. From that perspective, one of the closest studies in the literature is by Cortes (2016), who examines the effects of routinization on individual occupational transition patterns and provides empirical evidence of increased occupational mobility towards non-routine manual and non-routine cognitive jobs due to technological change. Further, Autor and Dorn (2009) specify demographic groups that are likely to be more affected by RBTC, while Cortes, Jaimovich, and Siu (2017) and Jaimovich et al. (2020) determine mobility patterns for specific social groups. In contrast to these studies, our paper focuses on the effects of RBTC on occupational choices and career progression over workers' lifetimes.

Among the studies that link occupational mobility with RBTC and job polarization, the study by Garcia-Penalosa, Petit, and Ypersele (2022) suggests that the disappearance of middle-wage occupations might negatively affect the occupational mobility of young workers with worse family background towards higher-paid jobs when they mature, due to the loss of stepping-stone opportunities. We consider our study complementary to that research, as our structural model allows us to quantify the contribution of technological change to the diminishing stepping-stone opportunities and the resulting probabilities of employment in higher-paid, high-skilled occupations across workers with different initial conditions.

Our structural model utilizes several ideas from Cortes (2016) and Jung and Mercenier (2014) regarding Roy-type occupational selection driven by comparative advantage. The modelling approach in these studies is able to generate an employment polarization pattern in response to RBTC defined as an exogenous shock in the static model. To study RBTC effects over life cycles, we incorporate elements of individual dynamics into the model structure: human capital accumulation and overlapping generations of workers. Structurally, our model shares some ideas with models of dynamic occupational choice from Keane and Wolpin (1997) and Yamaguchi (2012), and with the model of occupational mobility based on occupation-specific experience from Kambourov and Manovskii (2009). However, our approach differs from the first group of models as it allows for a potentially limited set of employment opportunities, and from the second model type as it focuses on RBTC as the key exogenous source of model dynamics.

3 RBTC and Career Paths

A decrease in the share of routine occupations in overall employment, observed in the process of routine-biased technological change, is directly associated with the lowering of employment opportunities in the respective occupations (Autor, 2010; Cortes, Jaimovich, and Siu, 2017). In the case of routine occupations used by younger workers as a stepping stone along their career paths towards other occupations, lower employment opportunities in routine occupations at the moment of labor market entry can limit the occupational mobility of workers, including the upgrading towards high-skilled NRC jobs.

In our analysis, we use data from the Panel Study of Income Dynamics (PSID), which collects the detailed demographic and socioeconomic information on U.S. households, including the employment and income histories of individual household members since 1968. The PSID samples were published annually from 1968 to 1996, and biannually starting from 1997.

Our study restricts the sample to household members who are aged 21 and older and have recorded employment information, including employment status and occupational affiliation. Specifically, the survey associates employed individuals with their primary occupations, which are coded with 1-digit (1968-1975), 2-digit (1976-1980), and 3-digit occupation codes (after 1981) at each interview year. In our study, the occupational codes are aggregated into four broad occupational categories[1]: non-routine cognitive (NRC), routine cognitive (RC), routine manual (RM), and non-routine manual (NRM), as described in Table 1.

Table 1: Major Occupations

Broad category	Occupation included	2000SOC
Non-routine cognitive (NRC)	Professional and technical workers	100-354
	Managers, business, and financial occupations	001-095
	Managers of retail and non-retail sales workers	470-471
Routine Cognitive (RC)	Sales workers, except managers	472-496
	Office and administrative support	500-593
Routine Manual (RM)	Construction and extraction	620-694
	Installation, maintenance, and repair	700-762
	Production occupations	770-896
	Transportation and material moving	900-975
Non-routine manual (NRM)	Service workers	360-465

Figure 1 demonstrates the employment shares of the four broad occupational groups across workers of different age, averaged across cohorts over the period from 1968 to 2015. According to the PSID, the majority of 21-year old workers tend to work in routine manual occupations (38%), followed by routine cognitive (31%), non-routine manual (20%), and non-routine cognitive (11%) occupations. Generally, experience and human capital requirements in NRC occupations are the highest; therefore, the share of this high-skilled employment is lower for younger workers. As workers get older, the share of employment in routine jobs declines, while the shares of non-routine manual and non-routine cognitive jobs demonstrate a U-shape and an inverted U-shape, respectively. This suggests an upward net-mobility towards high-skilled jobs in a prime age, as

[1]These standard categories are used in the seminal study by Cortes (2016), as well as in the follow-up research.

well as a downward net-mobility towards low-skilled jobs among workers who become closer to retirement.

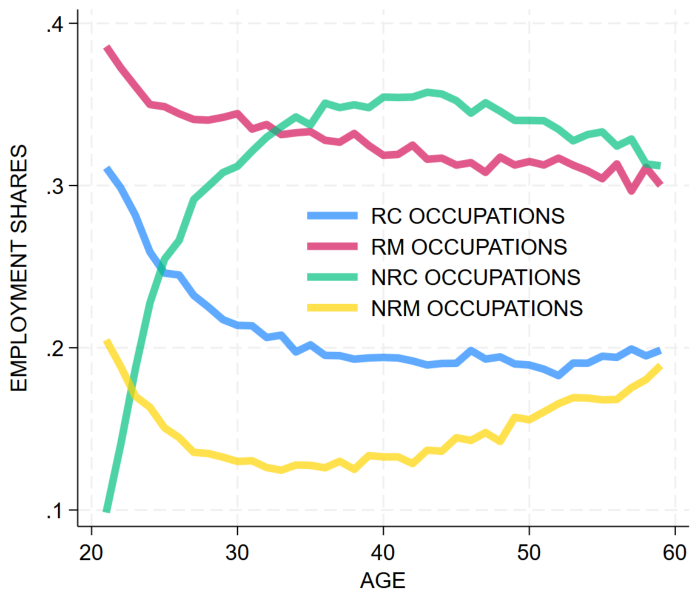

Figure 1: Employment shares in the three broad occupational categories over age

Long individual employment histories collected by the PSID provide an opportunity to examine the patterns of occupational mobility over the course of workers' lifetimes. To achieve this, we divide the working lifetimes of individuals into three distinct periods: when an individual is young (ages 21-30), of prime working age (31-50), or of older age (51-65). Further, we associate each lifetime period of every worker with a broad occupation in which they were predominantly engaged during that period.[2] As such, we reduce individual employment histories to broad occupational career paths.

Table 2 focuses on individuals who progressed towards non-routine cognitive occupations and counts feasible occupational paths observed in the data. Clearly, the dominant occupational path is "stationary" ($NRC \rightarrow NRC \rightarrow NRC$), i.e., such that workers start and end their careers in high-skilled jobs (50.11%). Other paths, however, indicate sizable occupational mobility towards NRC going through routine occupations: for example, there are 21.26% of individuals who were working in routine-cognitive occupations earlier in their lifetime and moved to NRC later on ($RC \rightarrow NRC \rightarrow NRC$ and $RC \rightarrow RC \rightarrow NRC$ occupational paths); the share of workers who were

[2]This is done by calculating a mode over all occupations in which a worker is observed in a given lifetime period.

employed in routine manual occupations being young and prime age, and later upgraded to NRC 10.87% ($RM \rightarrow NRC \rightarrow NRC$ and $RM \rightarrow RM \rightarrow NRC$ occupational paths). Overall, 36.18% of observed career paths towards NRC are going through routine occupations. All other paths observed in the data can be found in Appendix A, describing all observed career paths that end in NRC occupations (Table A.1), as well as in other labor states (Tables A.2 —A.5).

Table 2: Occupational paths towards non-routine cognitive occupations (NRC)

Occ. Path	**Share**	**N**
$NRC \rightarrow NRC \rightarrow NRC$	50.11%	643
$RC \rightarrow NRC \rightarrow NRC$	10.98%	141
$RC \rightarrow RC \rightarrow NRC$	10.28%	132
$RM \rightarrow NRC \rightarrow NRC$	5.61%	72
$RM \rightarrow RM \rightarrow NRC$	5.22%	67
$NRM \rightarrow NRC \rightarrow NRC$	4.20%	54
$NE \rightarrow NRC \rightarrow NRC$	2.49%	32
$NRM \rightarrow NRM \rightarrow NRC$	2.18%	28
Other transitions	8.88%	129
Total	100%	1283

Note: To calculate the three-stage occupational paths, we split the lifetime of individuals into 3 age periods: young (21-30 y.o.), prime age (31-50), and older (51-65 y.o.). Each career path follows: $Young \rightarrow Prime \rightarrow Older$ life cycle. Occupations are assigned to each age period of a worker as a mode over all occupations in which a worker is employed in the given age period. NE stands for non-employed individuals. We define a non-employed individual as the one spending most of the year being non-employed. The threshold for being non-employed for those above 30 y.o. is working less than 520 hours per year, and for those below 30 y.o. it is working less than 260 hours, to allow for part-time employment while in full-time education.

Meanwhile, the occupational patterns described above are subject to changes over time. On the one hand, RBTC contributes to increased mobility from routine to non-routine occupations, as noted by Cortes (2016). On the other hand, employment share in routine jobs is declining, making the transition of labor towards non-routine cognitive occupations through routine occupations potentially more restrictive for later cohorts.

To investigate the evolution of the occupational career paths across cohorts, we start with assessing the changes in individual switching patterns towards different occupations. For each individual i entering the labor market in a year t and belonging to a 5-year cohort c, we define an indicator $I_{itc}\left(occ_{>30}=E\right)$ that equals to 1 if that individual is observed in $E \in \{NRC, RC, RM, NRM, NE\}$ after the age of 30.[3]. Next, we set up the binary specification outlined below:

$$I^{*}_{itc} = \eta_0 + \boldsymbol{\omega} \cdot \boldsymbol{cohort_c} + \boldsymbol{\theta} \cdot \boldsymbol{ind\_ctrl_i} + \boldsymbol{\psi} \cdot \boldsymbol{agg\_ctrl_t} + \epsilon_{itc}, \tag{1}$$

so that

$$I^{*}_{itc} > 0, \quad \text{if } I_{itc}\left(occ_{>30}=E\right)=1,$$
$$I^{*}_{itc} \leq 0, \quad \text{if } I_{itc}\left(occ_{>30}=E\right)=0.$$

and estimate it separately for each state E. In equation (1), $cohort_c$ is a set of 5-year cohort dummies ($cohort^{y}_{c}$) indicating the years when individual workers were entering labor market. For example, for individuals entering the labor market between 1975 and 1980, $cohort^{1975}_{c}=1$, while $cohort^{1975}_{c}=0$ for individuals entering the labor market before 1975 and after 1980. ind_contrl_i denotes a vector of individual controls, including binary indicators for gender (male/female), educational attainment (college/no college), and race (white/non-white). The vector agg_ctrl_t comprises aggregate controls for GDP, unemployment rate, and the two types of physical capital (ICT and non-ICT), all measured as of the year t when individuals were entering the labor market.

We estimate the specification in equation (1) using logit estimator. Figure 2 illustrates the conditional changes in probabilities of being in NRC, RC, RM, NRM occupations, and in non-employment at an older age, calculated as the average marginal cohort effects. In particular, Panel A of Figure 2 demonstrates that workers entering labor markets after 1980 faced significantly lower chances of employment in the NRC occupations later in their working life compared to those entering before 1975. Moreover, the magnitudes of the estimated coefficients tend to increase over time in absolute terms, indicating that each subsequent cohort of workers, in general, had lower chances of joining NRC occupations than the previous one. Furthermore, Panels B, C, and D of Figure 2 illustrate changes in the probabilities of employment in routine cognitive, routine manual, and non-routine manual occupations, respectively. In particular, later cohorts of workers tend to have lower employment probability in routine cognitive and routine manual occupations. This can be largely attributed to the declining share of both types of routine jobs in overall employment.

[3]Here, we pull two age groups together to represent the employment later in the life cycle. This is done to obtain more precise estimates for particular cohorts, as the number of observations is dying out quickly for younger cohorts. Our results for old and prime age groups analyzed separately are qualitatively the same, but the coefficients are less precise

In contrast, the probability of employment in NRM occupations shows a significant increase across cohorts.

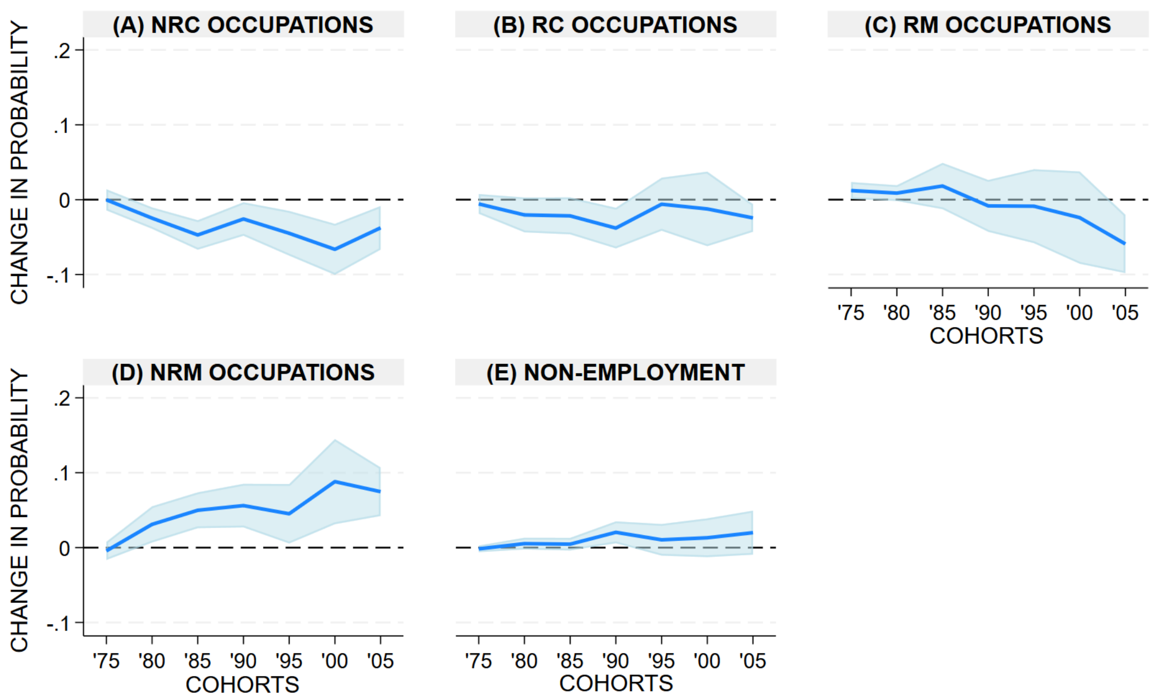

Figure 2: Changes by cohorts in the probability of being employed in a particular group of occupations in the prime to old age

Note: Each plot shows the point estimates for cohort effects (base cohort is < 1975) along with the 95% confidence intervals, estimated with a logit estimator and using average marginal effects. The specifications are controlling for individual characteristics (gender, education, race) and aggregate variables at the moment of labor market entry (real GDP, unemployment rate, capital shares of ICT and non-ICT capital). Standard errors are clustered at the cohort level.

To emphasize the connection between employment opportunities in routine occupations at labor market entry and the likelihood of switching to non-routine cognitive occupations later in the working lifetime, we combine PSID data with a new dataset on job ads published by Atalay et al. (2020). This dataset contains job ads from three major US newspapers (The Boston Globe, The New York Times, and The Wall Street Journal) over the period from 1940 to 2000, encompassing approximately 7.8 million observations. Atalay et al. (2020) map the textual content of vacancy postings to three-digit occupational codes, which can be then classified into the four broad occupational categories of interest from Table 1 (NRC, RC, RM, and NRM). Figure 3 shows how the the proportions of job ads attributed to the broad occupations change over the sample period, revealing a gradual increase in the share of NRC ads, while the shares of RC and RM ads are decreasing. At the same time, the share of ads for NRM jobs remains relatively stable from 1950 to 2000. We attribute these trends to the change in employment opportunities in the U.S. that is consistent with employment polarization observed since at least the 1980s[4].

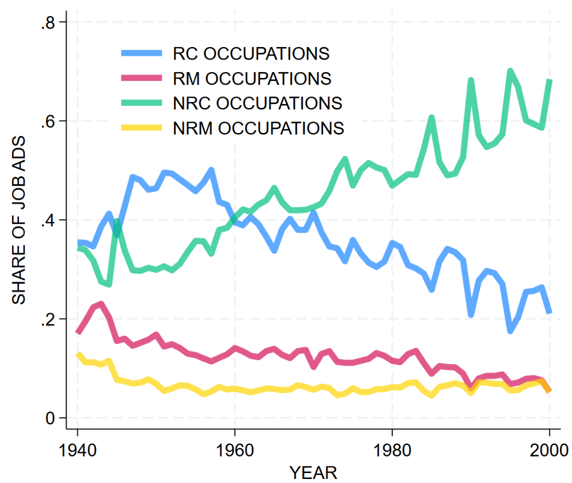

Figure 3: Shares of job ads by broad occupational groups, based on Atalay et al. (2020) data

We use the job ads data in the specification where we regress the indicator of being employed in the NRC occupation at an older age (50-65 y.o.) for an individual i on the labor market conditions in a year t when that individual entered the labor market for the first time, as well as a set of individual and aggregate controls as specified by equation (2).

$$\begin{aligned} I_{it}(occ_{old} = NRC) = &\eta_0 + \eta_1 \cdot RC\_adshare_t + \eta_2 \cdot RM\_adshare_t + \eta_3 \cdot NRC\_adshare_t + \\ &+ \gamma \cdot I_i(t \geq 1980) + \boldsymbol{\theta \cdot ind\_contrl_i} + \boldsymbol{\psi \cdot agg\_contrl_t} + \epsilon_{it} \end{aligned} \tag{2}$$

where $RC\_adshare_t$, $RM\_adshare_t$, and $NRC\_adshare_t$ are the shares of the respective job ads, as calculated using the data from Atalay et al. (2020). As these measures are based on vacancies posted by firms, they are indicative of the demand for routine and non-routine cognitive labor, and therefore of the employment opportunities in these occupational categories. We do not use employment shares of the broad occupational categories because they represent a combination of

[4]See Cortes (2016), and Acemoglu and Autor (2011) for further discussion of the timing of employment polarization

demand for routine or non-routine labor and corresponding labor supply by individuals. In our regression specification, we also add an indicator for year 1980 that is used as a threshold for the onset of labor market polarization.

Table 3 shows the estimation results for equation (2). Throughout columns (1)-(3), we estimate it as a linear probability model of being employed in a non-routine cognitive occupation at an older age. We start in column (1) with the regression specification featuring only the shares of job ads and an indicator for the start of polarization and then, by adding individual- and aggregate-level controls, arrive at the full specification in column (3). Column (4) shows the results obtained using logit estimator.

Table 3: Employment opportunities upon labor market entry and the probability of joining NRC occupation later in life

Dep. var.: probability of being in NRC when old	(1)	(2)	(3)	(4)
Share of RC job ads in the entry year	2.355**	1.937***	2.768***	3.024***
	(0.852)	(0.516)	(0.535)	(0.622)
Share of RM job ads in the entry year	3.596*	2.537*	2.969***	3.323***
	(1.707)	(1.213)	(0.769)	(0.917)
Share of NRC job ads in the entry year	2.672**	2.002***	2.376***	2.597***
	(0.795)	(0.488)	(0.428)	(0.491)
Entry year $\geq$ 1980	0.017	-0.001	-0.025**	-0.024***
	(0.032)	(0.026)	(0.007)	(0.007)
Individual Controls		✓	✓	✓
Aggregate Controls			✓	✓
Observations	7926	7926	7786	7786

Note: Columns (1)-(3) present the results from linear regressions, column (4) reports the results from logit regression, with average marginal effects reported. Individual controls: gender, race, education. Aggregate controls (in the labor market entry year): real GDP, unemployment rate, capital shares of ICT and non-ICT capital. Standard errors in parentheses * $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$. Standard errors in all specifications are clustered at a 5-year cohort level.

All three linear specifications show a positive and statistically significant correlation between the share of routine job ads in the entry year and the probability of being in NRC occupations when old. That is, the probability of being employed in NRC occupations by the end of the life cycle is significantly higher for those individuals who face higher employment opportunities in both types of routine occupations upon labor market entry. The sign on the threshold year coefficient is negative and also significant, suggesting that, controlling for other factors, the upward mobility towards NRC occupations has decreased in the era of labor market polarization. The results of the logistic regression, reported in column (4), are also similar to those in the linear specification. Note that the coefficient on the share of NRC job ads in the entry year is also significant. In this case, the underlying mechanism is potentially simpler: higher probability of joining NRC occupations around the entry year also implies that there will be more individuals who would remain attached to NRC occupations until the end of the life cycle.

In addition to considering the occupational categories in which workers were predominantly employed in one of the three lifetime periods, we can examine employment histories and exploit the occupational employment data in each period of workers' lifetimes. To support the proposed mechanism of routine occupations being used as the stepping stone for entering NRC occupations, we regress the indicator of being employed in NRC occupations when older on the indicator equal to 1 if an individual i is employed in an RC or RM occupation at a particular *age* and to 0 if employed in any other occupation (excluding NRC) or is in non-employment.

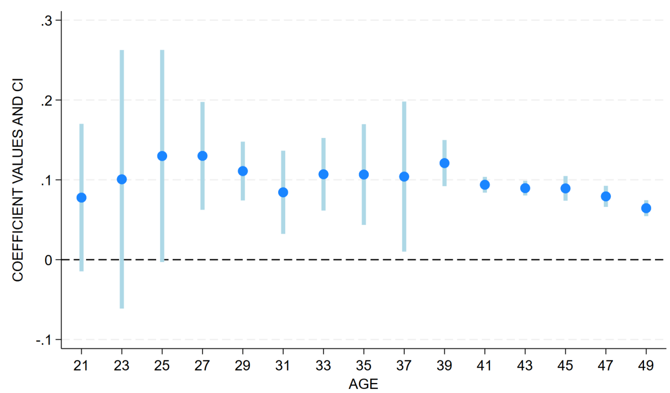

Figure 4: Correlation between the probability of entering NRC occupation when old and being in RC occupation when young(er)

Note: Each coefficient is obtained from a separate regression of the form: $I_{ic}(occ_{old} = NRC) = \psi_0 + \psi_1 I_i(occ_{age} = RC) + \boldsymbol{\psi_2 cohort_c} + \boldsymbol{\psi_3 year_i} + \boldsymbol{\zeta ind\_contrl_i} + \epsilon_{ic}$. The base category are the workers in either RM or NRM occupations or in non-employment. Blue dots are the point estimates of the ψ_1 coefficient, blue bars are the 95% confidence intervals. $\boldsymbol{year_i}$ stands for a vector of dummies for a year of observation of an individual i at a particular age. Individual controls: gender, race, education. Specifications are estimated using a linear estimator. Errors are clustered at the cohort level.

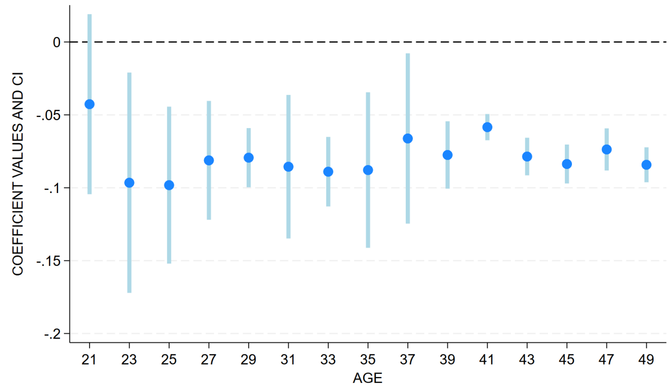

Figure 5: Correlation between the probability of entering NRC occupation when old and being in RM occupation when young(er)

Note: Each coefficient is obtained from a separate regression of the form:
$I_{ic}(occ_{old} = NRC) = \psi_0 + \psi_1 I_i(occ_{age} = RM) + \boldsymbol{\psi_2 cohort_c} + \boldsymbol{\psi_3 year_i} + \boldsymbol{\zeta ind\_contrl_i} + \epsilon_{ic}$.
The base category are the workers in either RC or NRM occupations or in non-employment.
Blue dots are the point estimates of the ψ_1 coefficient, blue bars are the 95% confidence intervals. For further details, see notes under Figure 4.

Figures 4-5 show the estimated coefficients on the indicator of being employed in RC or RM occupations from regressions that we run for workers of different age, before they turn 50. Comparison of the two figures reveals a further important detail of our analysis. Positive and statistically significant coefficients in Figure 4 suggest that, throughout a lifetime, being employed in RC occupations is positively correlated with the NRC employment at an older age. At the same time, Figure 5 shows that there is a negative correlation between being employed in RM occupations at a younger age and the probability of employment in NRC occupations later on.[5] We see this result as intuitively appealing. Experience in RM occupations, which often relies heavily on the use of physical skills, may not be applicable in high-skilled NRC cognitive occupations. On the other hand, relatively more skilled RC occupations are likely to be more efficient in the accumulation of human capital and experience relevant for the high-skilled NRC occupations.

Additionally, we estimate similar regression specifications for workers employed in NRM and NRC occupations, as well as for NE (see Figures B.1-B.3 in the Appendix). As we would expect, for younger workers, the probability of being employed in NRC occupations at an older age is positively

[5] At the same time, the interpretation for the positive correlation between the share of RM job ads upon labor market entry and the probability of being in NRC at an older age in Table 3 is given by our model. The calibrations of the model imply that human capital depreciation is slower in RM occupations than in NRM (used as a baseline ads category in Table 3), allowing workers from RM occupations to join NRC more freely compared to those from NRM.

correlated with employment in NRC occupations and negatively with employment in NRM occupations. Some positive correlations between being in non-employment and the probability of being in NRC at an older age are driven by workers previously employed in NRC occupations re-joining these occupations after an unemployment spell. Another possibility, which is later on reflected in our model, is that some of the workers in non-employment go through re-training to enhance their chances of joining NRC occupations.

The descriptive analysis in this section suggests that higher employment opportunities in routine occupations at the moment of labor market entry are associated with a higher probability of being observed in the NRC occupation later in life. The workers who manage to join the subset of routine occupations that are relatively more skilled, i.e., RC occupations, have a higher chance of being in NRC occupations in the future, potentially using RC occupations as stepping stones. With RBTC, employment opportunities in RC occupations are decreasing, resulting in a secular decrease in the probability of the stepping stone RC-to-NRC career path and potentially contributing to a bottleneck effect, whereby workers not starting their working life cycle in high-skilled NRC occupations either get stuck in lower skilled occupations or enter non-employment. In the following paragraphs, we develop a structural model, calibrate it using PSID and job ads data, and use it to establish the role of the stepping stone career path, as well as to quantify the potential bottleneck effect arising from RBTC.

4 The Model

Workers. The economy is populated by a continuum of risk-neutral individuals living for 3 periods: young ($a = 1$), prime ($a = 2$), and old ($a = 3$). In each period of lifetime, workers differ in their stock of human capital h_a and can work in one of the four occupations $j \in \{NRC, RC, RM, NRM\}$, earning $w_j(h_a)$. Workers can also be in non-employment ($j = NE$), receiving unemployment benefits $w_U(h_a)$[6]. Workers choose between the available employment and non-employment alternatives in each period in order to maximize their lifetime utility, i.e.:

$$\max_{\{j_a\}} E \sum_{a=s}^{3} \beta^{a-1} w_{j_a}(h_a) \tag{3}$$

[6]For simplicity, we assume unemployment benefits to be the same for all workers regardless of their human capital, i.e. $w_U(h_a) = w_U$. Making unemployment benefits dependent on human capital does not improve the model fit.

where j_a denotes occupational choice of an individual in period a.

The sorting into one of four employment alternatives is driven by several forces. First, we follow Jung and Mercenier (2014) and Cortes (2016) in assuming that occupational sorting is driven by comparative advantage. In particular, workers with higher human capital have higher earnings potential in NRC jobs, while workers with lower human capital levels have a comparative advantage in less skilled jobs, e.g., in NRM. Formally, we assume that earnings $w_j(h_a)$ are the product of the two components:

$$w_j(h_a) = \lambda_j \phi_j(h_a) \tag{4}$$

where the first component, λ_j, is a wage rate per efficiency unit in the occupation j, independent of the human capital stock. The second component, $\phi_j(h_a)$, is a non-decreasing function of a current human capital stock of a worker capturing the productivity of human capital h_a in the occupation j (in terms of efficiency units). For instance, the highest productivity of human capital in NRC occupations would imply that:

$$0 \leq \frac{\partial \ln \phi_j}{\partial h_a} < \frac{\partial \ln \phi_{NRC}}{\partial h_a} \;\; \forall h_a, \text{ where } j \neq NRC. \tag{5}$$

At the same time, for the supply of labor force to be non-zero in the other occupations, the high return on human capital in NRC occupations must be counterbalanced by the lower contribution of the component independent of human capital stock, i.e., λ_{NRC} must be below the corresponding values in occupations with lower productivity of human capital.[7] Under these conditions, workers with lower human capital stock sort into the occupations with higher λ_j and lower productivity of human capital, while workers with larger stocks of human capital choose NRC occupations.

In principle, we would expect the sorting between all the occupations to be driven by the differences in the two components determining wages, with the set of inequalities in (6) and (7) determining the occupational choices of workers with different levels of human capital. However,

[7] Alternatively, the non-zero supply in other occupations can be maintained by extremely low probability of job offer arrivals from NRC occupations. However, as is evident from the descriptive statistics presented in the previous section and the calibrations of the model below, such extremely low arrival rates are not supported by the data where a significant share of workers is employed in NRC occupations in every period of lifetime.

the sorting of workers across occupations is also driven by the rates of job offer arrivals from these occupational categories, as well as by the opportunities for human capital accumulation in each occupational category.

$$0 \leq \frac{\partial \ln \phi_{NRM}}{\partial h_a} < \frac{\partial \ln \phi_{RM}}{\partial h_a} < \frac{\partial \ln \phi_{RC}}{\partial h_a} < \frac{\partial \ln \phi_{NRC}}{\partial h_a} \;\; \forall h_a. \tag{6}$$

$$\lambda_{NRM} > \lambda_{RM} > \lambda_{RC} > \lambda_{NRC} > 0. \tag{7}$$

We introduce accumulation of human capital through learning-by-doing and allow for the rate of human capital accumulation (or depreciation) to differ across occupations. Specifically, human capital in the next period of lifetime is determined by:

$$h_{a+1} = b_j \cdot h_a, \text{ where } b_j \geq 0 \text{ and } j \in \{NRC, RC, RM, NRM, NE\} \tag{8}$$

Values of b_j above 1 imply that human capital is being accumulated over the course of a worker's employment in occupation j, while the values below 1 mean that a worker loses human capital while holding a given employment status.

Human capital accumulation, as well as its potential loss, highlight the importance of current employment status for workers' occupational choice and future career paths. On one hand, young and prime age individuals with relatively low stocks of human capital have incentives to choose occupations with higher λ_j, where the contribution of human capital stock to earnings is relatively low. On the other hand, they may raise their human capital stock through learning-by-doing and, in the following periods of lifetime, sort into occupations where productivity of human capital is higher. When accumulation of human capital is occurring in occupations that are also characterized by higher productivity of human capital, young and prime age workers may choose an occupation that returns lower earnings in the current period but is associated with a higher human capital accumulation and therefore higher earnings in future.

For instance, if the rate of human capital accumulation is higher in RC occupations than in RM and NRM occupations, young and prime age workers with relatively low human capital stock may prefer RC occupations over other occupations with potentially higher λ_j in order to increase their stock of human capital in future periods. In fact, workers may use the RC occupations as stepping-stones towards the NRC occupations. In this context, the *hollowing out* of employment opportunities in RC occupations may imply that less skilled younger workers, or the workers who did not receive an offer from NRC occupations, get "stuck" in low-skill jobs and lose opportunities to build and maintain enough of human capital to advance their career. This would then be described by what we term as a *bottleneck effect*: workers who are unable to secure employment in RC occupations to build and maintain their human capital until an offer from NRC occupations arrives would be more likely to be in NRM, RC, and RM occupations and non-employment at an older age than cohorts that were not exposed to the hollowing out of employment opportunities in RC occupations.

Occupational opportunities and occupational choice. Unlike in the standard polarization models, we allow for individuals observing only a *limited* number of employment opportunities. Specifically, in every period, each worker with probability p_j receives a new offer from an occupation $j \in \{NRC, RC, RM, NRM\}$, so that she encounters at most 4 new employment opportunities and chooses whether to remain in the current employment state or to switch to a new one out of the set of feasible choices. Additionally, in each period, a separation from the current job may occur with probability p_U. In that case, a worker can choose between non-employment state and whichever new job offers she receives in that period.

We assume that the arrivals of new job offers from different occupational categories are independent of each other (for example, a decline in p_{RC} does not change p_{NRC} and p_{NRM}). For a worker who was not separated from her current occupation, this implies 16 possible cases, depending on how many offers that worker receives. In particular, a randomly sampled worker may receive 4 offers from different occupational categories and choose from all possible employment opportunities. Alternatively, a worker may receive new offers in one or two different occupations, so that the set of feasible choices is narrower. Finally, a worker may receive no offers, so that the choice set of a worker would consist of only two opportunities: to remain in the current employment status or to become non-employed. Table 4 summarizes the possible cases (k) and their unconditional probabilities (q_k) given known p_{NRM}, p_{RM}, p_{RC}, and p_{NRC}.

Table 4: Employment opportunities

Case no.	# offers	Offers received	Case probability
$k = 1$	4 offers	NRC, RC, RM, and NRM	$q_1 = p_{NRC} \cdot p_{RC} \cdot p_{RM} \cdot p_{NRM}$
$k = 2$	3 offers	NRC, RC, and NRM	$q_2 = p_{NRC} \cdot p_{RC}$ $\cdot(1 - p_{RM}) \cdot p_{NRM}$
...	...	...	
$k = 6$	1 offer	NRC	$q_6 = p_{NRC} \cdot (1 - p_{RC})$ $\cdot(1 - p_{RC}) \cdot (1 - p_{NRM})$
...	...	...	
$k = 16$	no offers	-	$q_{16} = (1 - p_{NRC}) \cdot (1 - p_{RC})$ $\cdot(1 - p_{RM})(1 - p_{NRM})$

Employed individuals solve the lifetime utility maximization problem (3) by choosing one of three feasible opportunities: (i) either to stay in the current job; (ii) to switch to one of the offered jobs; or (iii) to shift to non-employment. Formally, the problem can be represented as a Bellman equation:

$$\begin{cases} V_{a,k}(h) = \max\limits_{j \in \{\text{choice set}\}} \left\{ w_j(h) + \beta E_k V_{a+1,k}(h' \mid j) \right\}, & \text{if } a = 1, 2; \\ V_{a,k}(h) = \max\limits_{j \in \{\text{choice set}\}} \left\{ w_j(h) \right\}, & \text{if } a = 3. \end{cases} \tag{9}$$

where E_k denotes the expectation of the future value over 16 possible cases described in Table 4, h is the current human capital stock of a worker, $(h'|j)$ is the level of next period human capital given the occupation in the current period.

Clearly, the problem falls into 16 cases that correspond to different realizations of the choice set. In Tables 5 and 6 we summarize the problems solved by individuals over the lifetime in each realized case. The older workers (Table 5) choose the option that returns the highest income $w_j(h)$ given their accumulated human capital h, since this is the last period of their working lifetime.

In contrast, young and prime age workers take into account the expectation of future value, which is defined as the average of value realization across 16 possible cases $V_{a,k}$ weighted by the probabilities of these cases q_k determined in Table 4, i.e.:

$$E_k V_{a,k}(h) = \sum_{k=1}^{16} V_{a,k}(h) q_k \tag{10}$$

Then, the young and prime age workers choose an option from a feasible choice set that maximizes current income plus discounted expected future value $E_k V_a(h)$.

Table 5: Value functions across realization of offer arrivals, older workers

Case no.	Offers	Value function $V_{3,k}(h)$
$k = 1$	NRC, RC, RM, and NRM	$V_{3,1}(h) = \max_{j \in \{C,NRC,RC,RM,NRM,NE\}} \{w_j(h)\}$
$k = 2$	NRC, RC and NRM	$V_{3,2}(h) = \max_{j \in \{C,NRC,RC,NRM,NE\}} \{w_j(h)\}$
...	...	...
$k = 6$	NRC	$V_{3,6}(h) = \max_{j \in \{C,NRC,NE\}} \{w_j(h)\}$
...	...	...
$k = 16$	-	$V_{3,16}(h) = \max_{j \in \{C,NE\}} \{w_j(h)\}$

Table 6: Value functions across realization of offer arrivals, young and mid-age workers

Case no.	Offers	Value function $V_{a,k}(h)$
$k = 1$	NRC, RC, RM, and NRM	$V_{a,1}(h) = \max_{j \in \{C,NRC,RC,RM,NRM,NE\}} \{w_j(h) + EV_{a+1}(h' \mid j)\}$
$k = 2$	NRC, RC, and NRM	$V_{a,2}(h) = \max_{j \in \{C,NRC,RC,NRM,NE\}} \{w_j(h) + EV_{a+1}(h' \mid j)\}$
...	...	...
$k = 6$	NRC	$V_{a,6}(h) = \max_{j \in \{C,NRC,NE\}} \{w_j(h) + EV_{a+1}(h' \mid j)\}$
...	...	...
$k = 16$	-	$V_{a,16}(h) = \max_{j \in \{C,NE\}} \{w_j(h) + EV_{a+1}(h' \mid j)\}$

Note: C in the choice sets corresponds to the current employment state

Technological Change. To model routine-biased technological change, we follow the intuition suggested by Autor (2010): new automaton technologies replace routine labour due to automation of routine tasks and "hollow out" employment opportunities in routine occupations. This specifically implies that after RBTC new routine job offers arrive to workers less frequently.

In the context of the model, a decline in routine employment opportunities is equivalent to a decline in the arrival of new offers from routine jobs p_{RC} and p_{RM}. As a result, these offers are less likely to appear in the individual choice sets, so that workers who could potentially do that job have to either choose another feasible job (i.e. NRM or NRC) or remain in non-employment. The lack of offers from RC occupation potentially limits the ability of these workers to maintain and build their human capital and to increase their comparative advantage in high-skill (NRC) jobs in the future.

5 Estimation

Model parametrization and simulation. The model is simulated biannually from 1942 until 2028, with 3 generations of workers (young, prime, and older) living simultaneously in any given year. The difference in the labor market entry year between young and prime workers, as well as between prime and older workers, is set to be equal to 14 years. In each run of the model, we simulate 43 cohorts of workers, with the first cohort of workers reaching the older age by 1970 (the beginning of the period targeted by calibration procedure) and the youngest cohort entering the labor market in 2000 (the end of the targeted period).

Each cohort consists of 10,000 simulated workers who are heterogeneous in their initial skill endowment and in the lifetime realizations of their job offer arrivals. To obtain the job choice decisions and the resulting human capital accumulation and earnings of each worker in the model, we recursively solve their remaining lifetime problems in each age. We set workers' expectations about the future values of arrival rates and wage equal to the values of the respective arrival rates and wages that they observe in their current age.[8]

[8] We also try an alternative specification where workers have perfect foresight about the values of $p_{j,t}$ and $\lambda_{j,t}$ in the coming periods of their lifetime. This specification of the model produces qualitatively and quantitatively similar results. However, we prefer the naive expectation specification over the perfect foresight since the former minimizes the effect of arrival rate values after the year 2000. We do not observe these values in the job ads data and therefore have to directly calibrate for them by either fixing these values on some average levels or by allowing for linear or non-linear time trends.

To introduce the secular changes in the economy that took place between 1970 and 2000 and which cannot be directly captured by our model, we allow for time-varying wage rates $\lambda_{j,t}$ in each of the 4 occupations, as well as for a time-varying separation rate $p_{U,t}$.[9] We calibrate wage rates and separation rates before 1970 and after 2000 to fixed values $\lambda_{j,pre}$ and $\lambda_{j,post}$, and $p_{U,pre}$ and $p_{U,post}$.

Further, we set the productivity of human capital to be an exponential function of the current human capital stock (Equation 11), with the parameter a_j capturing the differences in human capital productivity across occupations. The realizations of initial human capital stock for young workers are drawn from normal distribution with mean μ_{h_0} and variance $\sigma^2_{h_0}$.

$$\phi_j = exp(a_j h_a) \tag{11}$$

Additionally, in order for the model to produce an adequate sorting between RM and NRM occupations at older age, we have to introduce factor κ that scales down the utility of older workers employed in RM occupations. Our calibrations imply $\lambda_{RM,t}$ and $\lambda_{NRM,t}$ being similar in magnitudes and the productivity of human capital in RM occupations (a_{RM}) being above that of NRM occupations (a_{NRM}). As a result, RM occupations turn to be more attractive than NRM occupations and workers tend to sort more often into the former and less often into the latter by older age in the model simulations than in the data. While the focus of our model is on the lifetime movement of workers towards the NRC occupations, it lacks the explicit mechanisms potentially driving the lifetime sorting between the other occupational categories. The introduced factor κ can, among other things, represent the health costs faced by older workers in often physically demanding RM occupations (see Table 1) that are less present in other occupational categories.

Arrival rates. In our setting, the key source of variation in the outcomes of workers from different cohorts are the changes in the job offer arrival probabilities. We use the job ads data from Atalay et al. (2020) to recover the changes in the probabilities of job offer arrivals from NRC, RC, RM, and NRM occupations over time. We set the percentage changes in p_{NRC}, p_{RC}, p_{RM}, and p_{NRM} to follow the percentage changes in the number of job ads from the respective occupational

[9] Alternatively, instead of time-varying $\lambda_{j,t}$, we can set a_j to change over time. The results from both such model specifications tend to be the same. However, the model with both sets of parameters varying over time is not identifiable given our data.

categories (Figure 3), adjusted by the changes in the sample size of the Atalay et al. (2020) data. Formally, for any two adjacent years we set:

$$\frac{p_{j,t} - p_{j,t-1}}{p_{j,t-1}} = \Delta_{j,t} - \Delta_t \quad , \tag{12}$$

where $\Delta_{j,t}$ is the percentage change in the number of ads from occupational category j between years $t-1$ and t, and Δ_t is the percentage change in the total number of job ads between years $t-1$ and t. This way, we attribute all the differences between the changes in the number of ads from category j and the changes in the sample size to the changes in demand for jobs in occupational category j. Figure 6 shows the estimated changes relative to the base of 1944.

As captured by the changes in the number of job ads, the demand for routine occupations decreased over most of the sampling period. Demand for RC jobs showed growth for half a decade following World War II and decreased from the early 1950s until the end of the observation period of the Atalay et al. (2020) data in year 2000. Over the same period of time, it was shown by Eden and Gaggl (2018) that relative ICT capital prices decreased more than three times and ICT capital share increased from 0.63% in 1950 to 4.10% by 2000.

Demand for RM jobs fell from year 1944, with a slow-down between the second half of the 1950s until the early 1980s when the US economy witnessed a rapid decrease in demand for RM occupations due to industrial automation and offshoring. At the same time, NRC occupations grew at different rates from the 1940s until 2000 and demand for NRM jobs, after an initial fall in the 1940s-1950s and stagnation in the 1960s-mid 1970s, increased until the end of the observation period. The measured decreases in demand for routine occupations and increasing demand for non-routine occupations starting from the 1980s are in agreement with the observed labor market polarization (Autor and Dorn, 2013), reflecting the changes in the demand side of the economy leading to an increase of employment in high-skill (NRC) and low-skill (NRM) occupations.

In our model, the changes in demand depicted in Figure 6 are set to be equal to the changes in job opportunities, captured by the probabilities of job offer arrivals. The 4 initial probabilities, $p_{NRC,1944}$, $p_{RC,1944}$, $p_{RM,1944}$, and $p_{L,1944}$ are calibrated together with the rest of the model parameters. After 2000, the job offer arrival probabilities are set to be fixed at the respective year 2000 levels.

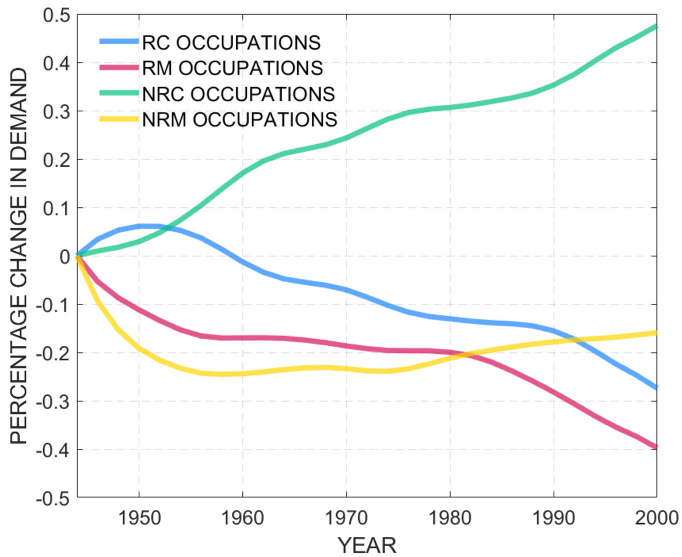

Figure 6: Changes in demand for jobs in 4 occupational categories
based on the Atalay et al. (2020) data

Note: The time series for demand changes are HP-filtered, using the smoothing parameter 100.

Targeted moments and identification. To calibrate the rest of the model parameters, we use the method of simulated moments. The vector of model parameters is chosen by the optimization procedure, using the combination of simplex search and pattern search methods, to minimize the sum of squared distances between the moments calculated from the simulations of the model and the corresponding data targets. Data moments used as targets are calculated using the same PSID data that we use in Section 3 and can be divided into three sets: (i) *Allocations* — shares of male workers from NRC, RC, RM, NRM and NE groups for young (21-30 y.o.), prime age (31-50 y.o.), and older (51-65 y.o.) workers; (ii) *Transitions* — average probabilities of switches between NRC, RC, RM, NRM and NE groups between young and prime age and between prime and older age; (iii) *Wages* — mean log-wages for young, prime-aged and older workers in NRC, RC, RM, and NRM occupational groups, normalized by the mean log wage of young NRC workers at the beginning of the targeted period.

The period that we target with our calibrations is from 1970 to 2000, including the period of the most significant decrease in the share of RC employment — from the end of the 1980s to 2000. Allocations and wages are calculated for every second year in the period. This, along with the average transition rates, leaves us with 482 data moments to be targeted by the model with 107 parameters[10] estimated through the method of simulated moments.

All parameters of the model are identified jointly to provide the best fit for the three kinds of data moments that we are targeting. However, some of the moments are particularly informative about the values of specific parameters. Allocations in different years and average transition rates of workers across 4 occupational categories and non-employment identify the probabilities of job offer arrivals at the beginning of the model period $p_{NRC,1944}$, $p_{RC,1944}$, $p_{RM,1944}$, and $p_{NRM,1944}$, separation rates in different years $p_{U,t}$ and the level of unemployment benefit w_u. Allocations of young workers across occupational categories, as well as wage profiles for young workers, help to pin down the parameters of the initial skill distribution.

Furthermore, transition rates from occupational categories where human capital productivity is lower to the occupations where productivity of human capital is higher identify the human capital accumulation parameters b_{RC}, b_{RM}, b_{NRM}, while the transition probabilities from non-employment towards less vs. more human capital productive occupations identify the b_{NE} parameter. For occupations characterized by higher productivity of human capital, e.g., NRC, human capital accumulation parameter is also informed by the growth of average wage profiles from young to older age.

The movements of wages across cohorts identify a host of $\lambda_{j,t}$ values and, along with the allocations, inform the values of human capital productivity in different occupations by creating a trade-off between the level of $\lambda_{j,t}$ and the level of a_j that ensures a non-zero labor supply in each of the occupational categories. An additional parameter κ is set to compensate for the excessive sorting of older workers to RM occupations (see the Model parametrization and simulation paragraph for details).

6 Results

Model fit. Figures 7-9 show the moments produced by the simulations of a model specification that delivers the best fit to the data. As can be seen from Figure 7, for most of the allocations of workers across the four occupational categories and non-employment, the model reproduces both trends and levels observed in the data. There is a slight overestimation of the share of older workers employed in NRC occupations, mirrored by a lower-than-in-the-data share of older workers

[10]Note, that each $\lambda_{j,t}$ and $p_{U,t}$ is calibrated as a separate parameter.

employed in NRM occupations. While the share of NRC workers at older age in the data is below that of the prime age for the most of the targeted period, our model produces the shares of older NRC workers close to those of prime age.[11] As more workers end up in NRC occupations in our calibrated model than in the data, there might be a downward bias in the estimated contribution of the stepping stone mechanism and bottleneck effect that we discuss in the paragraphs below. Therefore, all the estimates must be interpreted as a lower bound for the true effects of the hollowing out of employment opportunities in RC occupations.

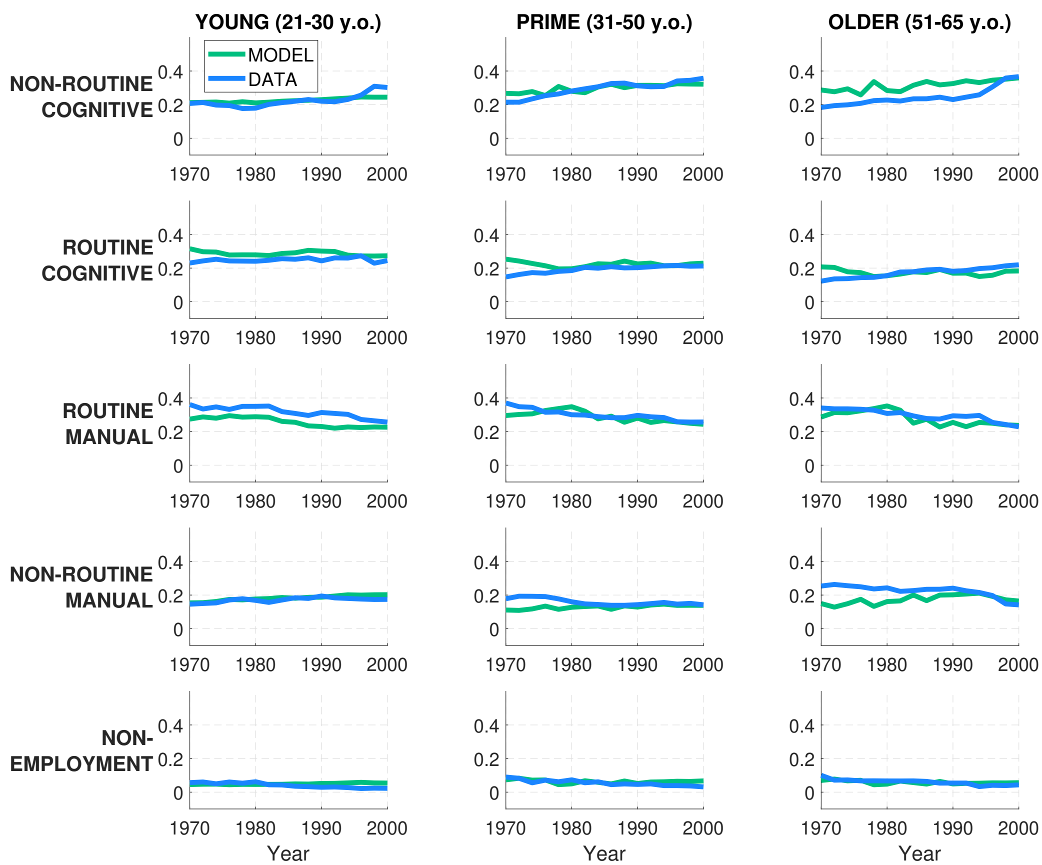

Figure 7: Model fit. Allocations.

Note: Data-based allocations for occupation X are calculated for each year and each age group as a share of workers who were assigned to occupation X as it was their most frequently observed occupation while they were in that age group. For each year and age group, occupational shares sum up to 1.

[11]This discrepancy is associated with a trade-off between matching the shares of older workers in NRC occupations and matching the average log-wage profiles for these workers. In the data, the average log-wage profiles of older workers do not decrease relative to those of prime age workers. While we could potentially introduce a depreciation of human capital in NRC occupations at older age, this would also lead to a lower average wage for older NRC workers.

For all occupational and age groups, the model is quite precise in reproducing the evolution of wages over the period from 1970 to 2000 (Figure 8), with only a minor overestimation of wages for young RM workers. Variation in wages across cohorts of workers employed in the same occupations is largely attributable to time-varying $\lambda_{j,t}$ parameters. It is also important that the model reproduces the upward shifts in the wage profiles as NRC and RC workers become older. These shifts are associated with increasing average levels of human capital over the lifetime of NRC and RC workers and, to a large extent, allow us to identify human capital accumulation parameters b_{NRC} and b_{RC}.

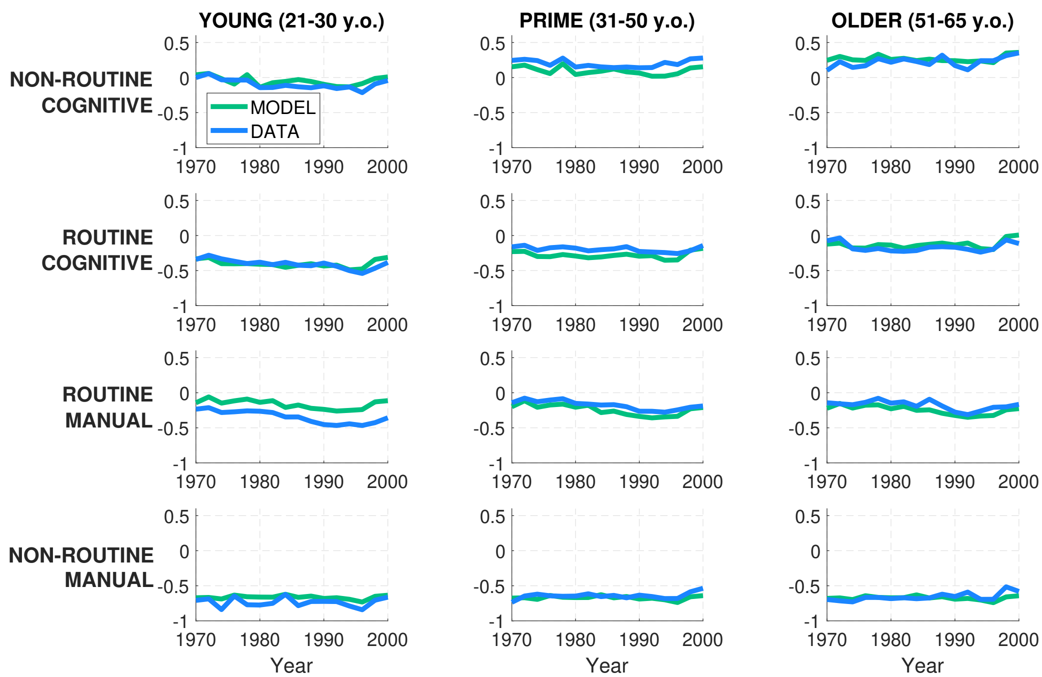

Figure 8: Model fit. Wages.

Note: Data-based wages for occupation X are calculated for each year and each age group as mean real log hourly wages in that year for workers who were assigned to occupation X as it was their most frequently observed occupation while they were in that age group. All wages are normalized to mean real log hourly wage of NRC workers in 1970.

Furthermore, as demonstrated by Figure 9, our model succeeds in reproducing the average probabilities for most of the possible transitions between the four occupational categories, as well as the non-employment state. Notably, for young and prime age workers, our model matches the data in reproducing higher probabilities of switches to NRC occupations for workers employed in RC occupations than for workers employed in RM and NRM occupations. This difference in the switch probabilities is in line with the proposed stepping stone role of RC occupations and is captured in the model through the accumulation of human capital in RC occupations and depreciation of human capital in RM and NRM occupations.

Additionally, there is a high probability of switching to NRC occupations for those in NE. Although a significant share of these transitions is due to high human capital workers previously separated from NRC occupations re-joining this occupational category, the higher transition rate is further supported by the fact that human capital is not depreciating in NE and is even slowly accumulating while workers are in non-employment.

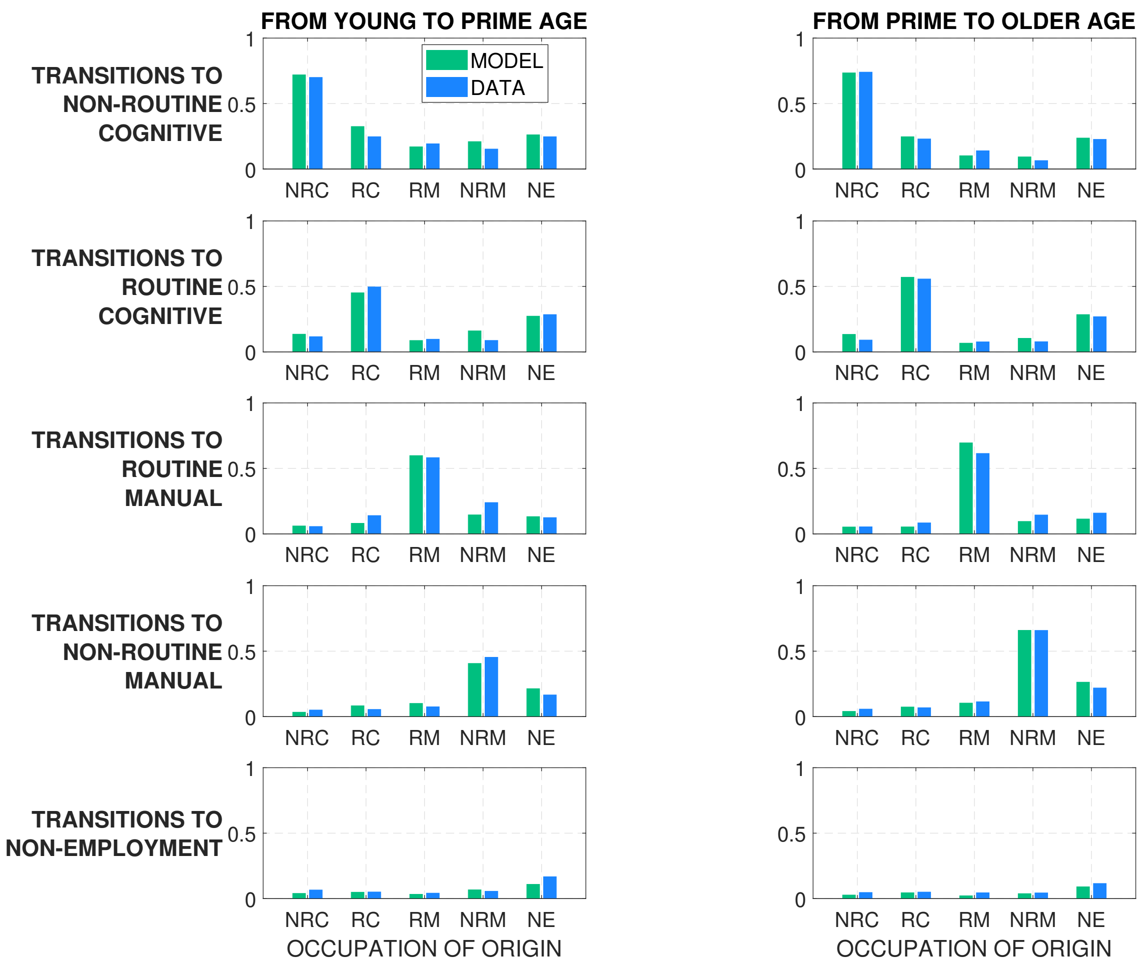

Figure 9: Model fit. Transition probabilities.

Note: Transition probabilities are calculated as a probability of switching to a target occupation Y in the next period of lifetime conditional on being in occupation X in the current period of lifetime. For each occupation of origin and age group, transition probabilities sum up to 1.

Estimated parameters. Table 7 consolidates the parameters of the model that provide the best fit of the moments produced by the model simulations to the corresponding data moments. As one could expect, the accumulation of human capital is occurring at the fastest rate in NRC occupations: spending one model period (equal to 14 years of working lifetime) in NRC occupations results in a 34% increase in a worker's human capital stock. Outside of NRC occupations, the estimated human capital accumulation coefficients imply that employment in RM and NRM occupations leads to a depreciation of human capital of a worker: 20% and 52% of lost human capital stock per model period, respectively. In contrast, for workers choosing RC occupations, there is a 19% increase in human capital stock per model period, which renders RC occupations the second most favorable broad occupational category for human capital accumulation. Model calibration also implies that there is a certain human capital accumulation occurring in non-employment, with workers going through re-qualification courses and, especially the younger ones, being enrolled in full-time education.[12]

Growth of human capital stock in NRC and RC occupations and its loss in RM and NRM occupations suggests that human capital in our model should be interpreted not as general human capital, but rather as a specific, cognition-related kind of human capital, such as quantitative reasoning or ability to comprehend larger written texts. According to the estimated human capital returns, this cognition-related human capital is highly demanded in NRC and RC occupations, where intensity of its use allows workers to further accumulate it through learning-by-doing. It is much less demanded, however, in RM occupations and is almost unproductive in NRM occupations where it depreciates at the highest rate.[13]

It should be noted that the estimated returns to human capital in RC occupations are even higher than in NRC occupations. In the model, these high returns to human capital compensate for low $\lambda_{RC,t}$ (Figure C.1 (B)) making workers with intermediate levels of human capital prefer RC occupations over RM and NRM occupations. In fact, even workers with higher human capital

[12]In the data used for the calibration of the model, we pull together individuals who are not employed due to exogenous separation (and whose human capital is likely to depreciate) and also those who do not participate in the labor force due to full-time education, as well as those who were exogenously separated but are going through re-qualification to improve their employment opportunities. We therefore expect the b_{NE} parameter to be the average of human capital changes for these groups of non-employed workers.

[13]In fact, this result is in agreement with the intuition provided by the studies considering mutlidimensional human capital (Sanders and Taber, 2012; Yamaguchi, 2012; Lise and Postel-Vinay, 2020). For instance, Lise and Postel-Vinay (2020) show that the three types of skill — cognitive, manual, and interpersonal — represent distinct productive characteristics of a worker that are valued differently across occupations and are accumulated faster in the occupations where they are used more intensively.

stock may end up in RC occupations as the probability of job offer arrival from NRC occupations is one of the lowest (Figure C.2). For the workers who manage to join NRC occupations, lower returns to human capital are compensated by its much faster accumulation.

Table 7: Estimated parameters

Parameter Description	Parameter Notation	Value	Comments
Discount factor	β	0.54	0.96 yearly discount rate
Human capital returns	$\{a_{NRC}, a_{RC}, a_{RM}, a_{NRM}\}$	$\{1.07, 1.2, 0.65, 0.04\}$	
Occupational wage rate in NRC	$\{\lambda_{NRC,t}\}_{t=1970...2000}$	$[0.98, 1.22]$	Figure C.1 (A)
Occupational wage rate in NRC before 1970	$\lambda_{NRC,pre}$	1.15	
Occupational wage rate in NRC after 2000	$\lambda_{NRC,post}$	0.99	
Occupational wage rate in RC	$\{\lambda_{RC,t}\}_{t=1970...2000}$	$[0.78, 0.95]$	Figure C.1 (B)
Occupational wage rate in RC before 1970	$\lambda_{RC,pre}$	0.66	
Occupational wage rate in RC after 2000	$\lambda_{RC,post}$	0.99	
Occupational wage rate in RM	$\{\lambda_{RM,t}\}_{t=1970...2000}$	$[1.34, 1.62]$	Figure C.1 (C)
Occupational wage rate in RM before 1970	$\lambda_{RM,pre}$	1.50	
Occupational wage rate in RM after 2000	$\lambda_{RM,post}$	1.44	
Occupational wage rate in NRM	$\{\lambda_{NRM,t}\}_{t=1970...2000}$	$[1.36, 1.52]$	Figure C.1 (D)
Occupational wage rate in NRM before 1970	$\lambda_{NRM,pre}$	1.38	
Occupational wage rate in NRM after 2000	$\lambda_{NRM,post}$	1.39	
Human capital accumulation	$\{b_{NRC}, b_{RC}, b_{RM}, b_{NRM}, b_{NE}\}$	$\{1.34, 1.19, 0.80, 0.48, 1.1\}$	
Initial human capital distribution	$N(\mu_{h_0}, \sigma^2_{h_0})$	$N(0.86, 0.32)$	
Arrival rates in 1944	$\{p_{NRC,1944}, p_{RC,1944}, p_{RM,1944}, p_{NRM,1944}\}$	$\{0.17, 0.59, 0.41, 0.65\}$	Figure C.2
Separation Rate	$\{p_{U,t}\}_{t=1970...2000}$	$[0.29, 0.56]$	Figure C.3
Separation rate before 1970	$p_{U,pre}$	0.41	
Separation rate after 2000	$p_{U,post}$	0.34	
Unemployment Benefit	w_U	0.30	
Utility scaling factor for older RM workers	κ	0.84	

Turning to the estimated job offer arrival rates (Figure C.2), the model calibrations suggest that the highest employment opportunities over the targeted period are in RC and NRM occupations, with the employment opportunities in NRM occupations overtaking those in RC occupations in the early 1980s. Employment opportunities in RM occupations are the third highest, but become almost equal with the growing employment opportunities in RC occupations by the end of the targeted period. The observed allocations of workers across occupational categories and non-employment are an outcome of workers observing the employment opportunities in each category and then sorting across occupations in accordance with their human capital stock and the opportunities of human capital accumulation.

Contribution of the stepping stone mechanism. First, to establish the contribution of the stepping stone mechanism to workers' movement toward NRC occupations over the working lifetime, we compare the fully calibrated model discussed in the previous paragraphs to the model with no stepping stone mechanism. The model with no stepping stone mechanism has the same parameter values as the full model with the only exception that we set the human capital accumulation in RC occupations to be equal to human capital accumulation in RM occupations, i.e., we set $b_{RC} = b_{RM}$. This way, we switch off the incentive for higher human capital workers, who do not have an opportunity to be employed in NRC occupation in the current period, to join RC occupations to accumulate human capital (instead of losing it in RM and NRM occupations) and to join NRC occupations once, and if, an offer arrives therefrom. In the model with no stepping stone mechanism, the choice between RC, RM, and NRM occupations is driven only by a worker's current amount of human capital and the wage rates $\lambda_{j,t}$ in the respective occupations.

Panel (A) of Figure 10 compares the shares of young workers who will switch to NRC occupations by older age in the full model with the same share in the model with no stepping stone mechanism. For each year, the difference between the solid and dashed lines gives the share of workers in the full model following the stepping stone career path — first joining RC occupations, maintaining and accumulating their human capital there and switching to NRC occupations when an offer arrives later in the working lifetime. The average share of such workers over the period from the entry of the model's oldest cohort to the entry of the model's youngest cohort is 6%. This means that, on average, 6% of all workers observed in NRC occupations by older age reach these occupations through the stepping stone career path.

We also note that the removal of human capital accumulation incentives exposes a downward trend in the share of workers moving towards NRC occupations through RC occupations. In the full model, increasing expected returns to human capital, associated with increasing employment opportunities in NRC occupations, motivates workers unable to join NRC occupations in the current period to take offers from RC occupations more frequently. These growing incentives mask a decrease in the RC employment opportunities.

Panel (B) of Figure 10 shows the share of all young workers who will end up in NRC occupations by older age. Again, the difference between the lines produced by the full model and the model with $b_{RC} = b_{RM}$ shows the contribution of the stepping stone mechanism. For instance, according to the model, 1.8% of the 1980 young labor force chose to follow the stepping stone career path towards NRC occupations. Given the level of the labor force in 1980,[14] this percentage implies that only out of the labor force aged 20-24 there were approximately 288 thousand workers choosing this path. With the new cohorts continuously entering the labor market and choosing different subsequent career paths, the cumulative share of workers choosing stepping stone career paths accounts for a substantial share of the total labor force.

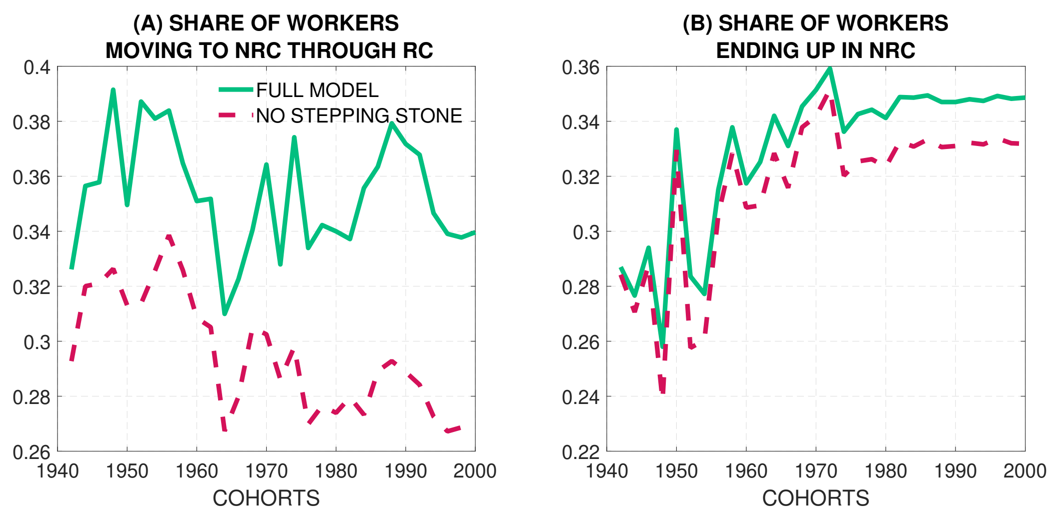

Figure 10: Workers' transitions to NRC occupations by older age in full and no stepping stone models

Note: No stepping stone model is simulated under the human capital accumulation in RC (b_{RC}) occupations set equal to human capital accumulation in RM (b_{RM}). All other parameters in the no stepping stone model are the same as in the full model.

[14]https://fred.stlouisfed.org/series/LNS11000036

An alternative way to see the importance of the stepping stone mechanism is to set $b_j = b_{RC}$ $\forall$ j, so that workers could accumulate human capital in all occupations with the same speed as in RC occupations. This way, it would be possible to use employment in all occupations as stepping stones towards NRC occupations, while the choice from the available occupations would be solely driven by workers' current level of human capital and by the respective $\lambda_{j,t}$. Figure D.1 in the Appendix compares the results of simulations under b_j fixed across all occupations with the simulations of the full model. Similarly to Figure 10, the share of workers moving to NRC through RC occupations is lower in the model with b_j fixed across all occupations than in the full model. Workers do not have additional incentives to join RC occupations and choose occupations where their current wage is higher. At the same time, as suggested by Panel (B) of Figure D.1, compared to the full model, the share of workers ending up in NRC occupations would be up to 4.7 p.p. higher if workers could accumulate human capital in all labor market statuses as effectively as in RC occupations.

Bottleneck effect. To determine whether a fall in the employment opportunities in RC occupations makes a substantial number of workers incapable of reaching NRC occupations later in the life cycle, we compare the full model with its counterfactual, simulated under the job offer arrival probabilities $p_{RC,t}$ fixed at its 1944 level. In simulations with fixed $p_{RC,t}$ workers do not face a decline in R employment opportunities and can follow the stepping stone career path throughout the whole model period at the same rate as at the beginning of the model period. The potential bottleneck effect in this counterfactual model is therefore absent — workers do not get stuck in NRM, RM occupations and non-employment, unable to reach the NRC occupations by maintaining and accumulating human capital in RC occupations.

Under the counterfactual simulations, in the presence of a substantial bottleneck effect, we would expect the share of workers observed in NRC occupations by older age to rise, as compared to the full model. This would imply that the NRC occupations are receiving less workers of older age because of a lower share of the workers being able to follow the stepping stone career path at earlier stages of their life cycle. Indeed, as demonstrated by Panel (A) of Figure 11, comparing the shares of workers ending up in NRC occupations by older age, a fall in RC employment opportunities is associated with a lower share of older workers joining NRC occupations by older age.

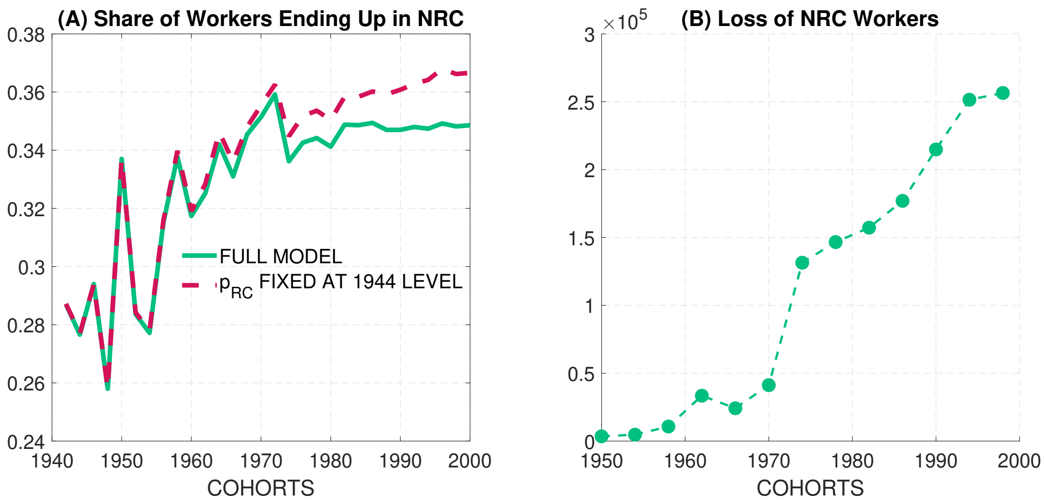

Figure 11: Workers' transitions to NRC occupations by older age in full and fixed $p_{RC,t}$ models

Note: For panel (A), all parameters in the counterfactual model are the same as in the full model, besides the job offer arrival rates from RC occupation that in the counterfactual model are fixed at the level of year 1944. For panel (B), the loss of workers is calculated using the youngest 20-24 y.o. civilian labor force (data from fred.stlouisfed.org/series/LNS11000036) in each year and taking the share of it implied by the percentage point difference between the full model and the counterfactual model from panel (A).

A bottleneck effect becomes apparent starting from the cohorts entering the labor market in the early 1970s. The full model implies a stagnation in the shares of workers reaching NRC occupations for cohorts entering the labor market after 1980. At the same time, in the counterfactual simulations where there was no decrease in RC employment opportunities, the share of workers joining NRC occupations by older age continues to grow. The bottleneck effect therefore becomes progressively more pronounced for the cohorts of workers entering after 1980. This result is consistent with our estimations on the PSID data (Panel (A) of Figure 2), where we show that, controlling for individual characteristics and aggregate conditions upon labor market entry, starting from 1975, younger cohorts of workers were progressively less likely to join NRC occupations in the later stages of the working lifetime.

To give some illustration for the magnitude of the bottleneck effect, Panel (B) of Figure 11 transforms the percentage difference between the full and the counterfactual model into the number of NRC workers lost due to a decline in the RC employment opportunities. We calculate it as a percentage of the youngest, and therefore closest to the labor market entry, 20-24 y.o. civilian labor force every 4 years.[15] The number of the youngest workers not joining NRC occupations at older age due to decreasing employment opportunities in RC occupations increased from around 42 thousand workers in 1970 to 256 thousand in 2000. Overall, our model implies that a fall in RC employment opportunities in the period from 1970 to 2000 resulted in more than 1.37 million lost NRC workers.[16] We can further compare this number with the net gain in the NRC workers over the studied years, obtained as the difference between the shares of workers ending up in NRC occupations in full model and in the model with all arrival rates fixed at their respective 1944 levels (see Figure D.2 in the Appendix). This comparison suggests that, if not for the bottleneck effect, the gain in the number of workers ending up in NRC occupations would be higher by approximately 12%.[17]

Alternative paths towards NRC. Despite a substantial decrease in employment opportunities in RC occupations, workers can avoid a bottleneck and try to reach NRC occupations through alternative career paths. Panel (A) of Figure 12 compares the shares of workers moving towards NRC through occupations other than RC in the full model simulations, where $p_{RC,t}$ is falling as suggested by the job ads data, and the same shares obtained from the simulations with $p_{RC,t}$ fixed at its 1944 level. The differences in the shares produced by the two model versions suggest that the fall in RC employment opportunities is partially compensated by workers choosing alternative career paths towards NRC occupations. In fact, for the youngest cohort in our simulations, an 8.2 p.p. higher share of workers reaching NRC occupations through alternative career paths in the full model suggests that a significant share of those who would otherwise follow a stepping stone career path is still able to reach NRC occupations even under considerably lower employment opportunities in RC occupations.

Panels (B) through (E) of Figure 12 compare the shares of workers following some of the most frequent alternative career paths towards NRC occupations in the full model with the corresponding shares in the counterfactual with fixed $p_{RC,t}$. In the full model, with $p_{RC,t}$ following the trend in the job ads data, workers start joining NRC occupations from the first period of their lifetime more frequently (1.8 p.p. increase vs. counterfactual by 2000, Panel (B)), as well as to choose NE as the labor market state in which they can accumulate human capital in the absence of offers from RC

[15] We calculate it with 4-year intervals to avoid potential double-counting.

[16] This figure is likely to be significantly higher, because in our calculations we use only each 4th year of the labor force data and also only some of the youngest workers entering the labor market.

[17] As suggested by Figure D.2, changes in employment opportunities across 4 occupational categories in the period from 1970 to 2000 led to a net gain of more than 11.45 million of NRC workers.

and NRC occupations (1.1 p.p. increase vs. counterfactual by 2000, Panel (E)). However, the most substantial increases in the frequencies of alternative career paths in the full model, as compared to the counterfactual, are associated with RM and NRM occupations: 3.1 p.p. and 2.3 p.p. by 2000, respectively (Panels (C) and (D)).

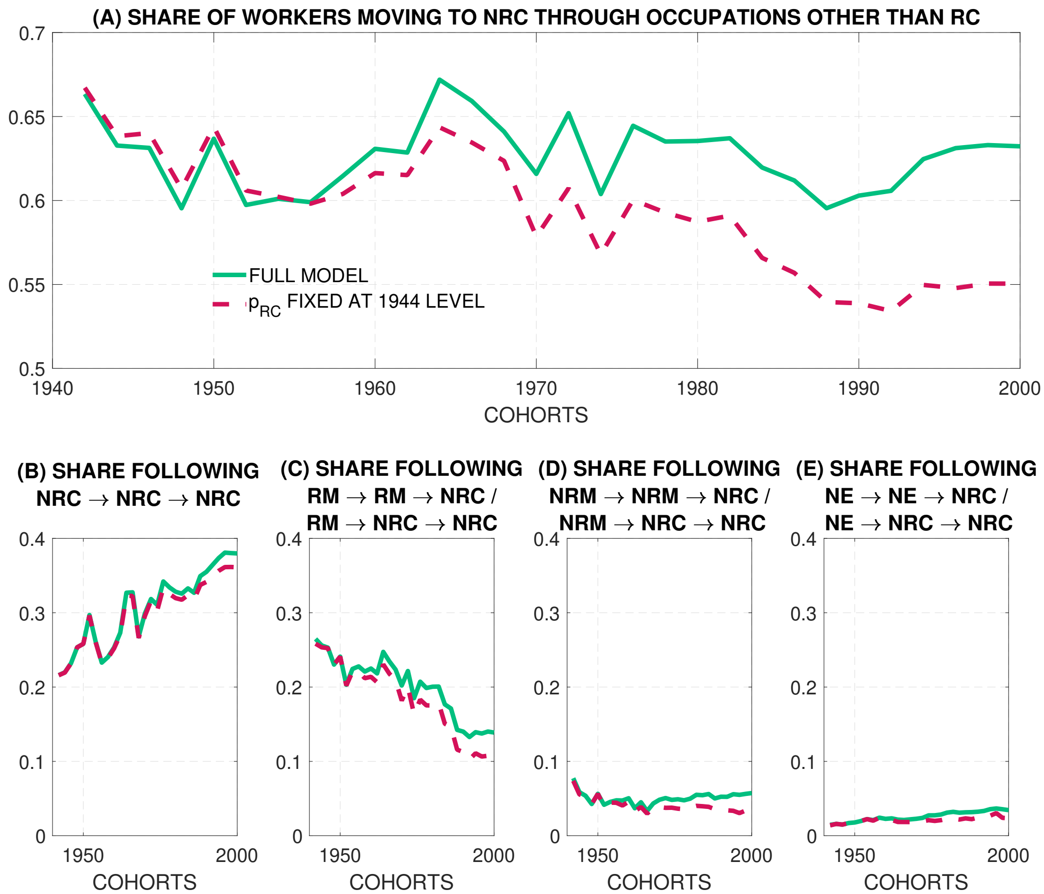

Figure 12: Alternative ways to reach NRC occupations

Table 8: Wage loss in NRC due to lower RC employment opportunities

	All		5th quantile		25th quantile		50th quantile		95th quantile	
	1980	2000	1980	2000	1980	2000	1980	2000	1980	2000
Prime	0.6%	1.8%	2.1%	2.9%	0.9%	3.2%	0.5%	2.6%	0.2%	0.4%
Older	0.5%	2.5%	1.1%	3.1%	0.6%	4.7%	1.4%	5.0%	0.6%	1%

As more workers are now moving towards NRC occupations through the labor market states associated with the depreciation of human capital (i.e., RM and NRM occupations), we would expect it to have an effect on the workers' productivity and wages once they join NRC occupations. Table 8 summarizes the NRC workers' wage loss due to a larger share of these workers employed in RM and NRM occupations at earlier stages of life. Overall, by year 2000, prime age workers were, on average, earning 1.8% less than they would if they could join RC occupations more frequently at a younger age. The average wage loss for older workers is 2.5% and is larger than for prime age workers because, on average, older workers manage to spend more time in RM and NRM occupations and, hence, experience larger average depreciation of human capital.

The effect of decreasing RC employment opportunities appears to change non-linearly across the NRC wage distribution. Those at the top of the distribution experience the least amount of negative effects, with the wage loss for older workers from the 95th percentile being equal to 1%. Workers from the lower end of the NRC wage distribution experience larger negative effects (up to 3.1% by older age for the 5th percentile). However, the most significant wage loss is suffered by NRC workers from the middle of the wage distribution (up to 5% for an older median worker). The negative effects are most pronounced for workers in the middle of the wage distribution because these workers are the ones most reliant on stepping stone career paths. At the same time, the top earners in NRC occupations are the ones who, in most cases, join NRC occupations from the beginning of their lifetime and do not have to go through other labor market states. The negative effect on the workers from the lower end or the NRC wage distribution is less due to these workers having lower human capital stock and their earning being, to a larger extent, determined by wage rate $\lambda_{NRC,t}$.

7 Conclusion

In this study, we argue that a decrease in routine employment, associated with routine-biased technological change (RBTC), can affect younger workers' chances of following a *stepping stone* career path from routine to the high skilled non-routine cognitive (NRC) occupations. We use PSID data and data on job ads to show the presence of career paths from routine to NRC occupations. We suggest that the hollowing out of routine employment is diminishing opportunities to maintain and accumulate human capital in relatively more skilled routine cognitive (RC) occupations and may affect the probability of joining NRC occupations later in life. Instead, workers who are unable to upgrade to NRC occupations through the disappearing RC occupations get stuck in less skilled occupations or enter non-employment. We term the congregation of workers in less skilled occupations and non-employment and the resulting potential loss of older NRC workers, coming from a decline in RC employment opportunities, as a *bottleneck effect*.

We develop a model with occupational choice and accumulation of human capital that endogenously generates the RC-to-NRC career path. We calibrate the model on PSID and job ads data and show that RC occupations can help workers to accumulate human capital relevant for NRC occupations. We then run counterfactual exercises to establish the role of the stepping stone career path and the potential bottleneck effect. We demonstrate that, on average, 6% of all workers observed in NRC occupations by older age reach these occupations through the stepping stone career path. A decline in RC employment opportunities over the years of the most active development of RBTC led to a loss of more than 1.37 million NRC workers who got stuck in lower skilled occupations, such as routine manual (RM) and non-routine manual (NRM), as well as in non-employment. A significant share of workers, however, avoid the bottleneck, reaching NRC occupations through RM and NRM occupations. The depreciation of human capital associated with following these alternative career paths results in wage loss once workers reach NRC occupations. The wage loss, associated with lower human capital, is most pronounced in the middle of the NRC wage distribution.

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Appendix A Career Paths. Four Broad Occupations

Table A.1: Occupational paths towards non-routine cognitive occupations (NRC)

Occ. Path	**Share**	**N**
$NRC \rightarrow NRC \rightarrow NRC$	50.11%	643
$RC \rightarrow NRC \rightarrow NRC$	10.98%	141
$RC \rightarrow RC \rightarrow NRC$	10.28%	132
$RM \rightarrow NRC \rightarrow NRC$	5.61%	72
$RM \rightarrow RM \rightarrow NRC$	5.22%	67
$NRM \rightarrow NRC \rightarrow NRC$	4.20%	54
$NE \rightarrow NRC \rightarrow NRC$	2.49%	32
$NRM \rightarrow NRM \rightarrow NRC$	2.18%	28
$NRC \rightarrow RC \rightarrow NRC$	1.32%	17
$RM \rightarrow RC \rightarrow NRC$	1.16%	15
$NE \rightarrow RC \rightarrow NRC$	1.01%	13
$NRC \rightarrow NE \rightarrow NRC$	0.93%	12
$NRM \rightarrow RC \rightarrow NRC$	0.70%	9
$RM \rightarrow NRM \rightarrow NRC$	0.54%	7
$NRC \rightarrow RM \rightarrow NRC$	0.46%	6
$RC \rightarrow RM \rightarrow NRC$	0.46%	6
$RC \rightarrow NRM \rightarrow NRC$	0.46%	6
$NRC \rightarrow NRM \rightarrow NRC$	0.38%	5
$NRM \rightarrow RM \rightarrow NRC$	0.31%	4
$NRM \rightarrow NE \rightarrow NRC$	0.31%	4
$NE \rightarrow NE \rightarrow NRC$	0.31%	4
$NE \rightarrow NRM \rightarrow NRC$	0.23%	3
$RC \rightarrow NE \rightarrow NRC$	0.15%	2
$NE \rightarrow RM \rightarrow NRC$	0.07%	1
$RM \rightarrow NE \rightarrow NRC$	0%	0
Total	100%	1283

Source: Authors' calculations on the PSID data

Table A.2: Occupational paths towards routine cognitive occupations (RC)

Occ. Path	**Share**	**N**
$RC \rightarrow RC \rightarrow RC$	39.76%	336
$NRC \rightarrow NRC \rightarrow RC$	11.47%	97
$RM \rightarrow RM \rightarrow RC$	6.86%	58
$NRC \rightarrow RC \rightarrow RC$	6.15%	52
$RC \rightarrow NRC \rightarrow RC$	5.91%	50
$RM \rightarrow RC \rightarrow RC$	5.79%	49
$NRM \rightarrow RC \rightarrow RC$	4.49%	38
$NRM \rightarrow NRM \rightarrow RC$	3.90%	33
$NE \rightarrow RC \rightarrow RC$	3.78%	32
$RM \rightarrow NRC \rightarrow RC$	1.77%	15
$RC \rightarrow RM \rightarrow RC$	1.30%	11
$RC \rightarrow NRM \rightarrow RC$	1.30%	11
$NRM \rightarrow NRC \rightarrow RC$	1.30%	11
$RM \rightarrow NRM \rightarrow RC$	1.18%	10
$NRC \rightarrow RM \rightarrow RC$	0.94%	8
$NE \rightarrow NRM \rightarrow RC$	0.94%	8
$NRM \rightarrow RM \rightarrow RC$	0.71%	6
$NRC \rightarrow NRM \rightarrow RC$	0.59%	5
$NE \rightarrow NRC \rightarrow RC$	0.47%	4
$NE \rightarrow RM \rightarrow RC$	0.35%	3
$NE \rightarrow NE \rightarrow RC$	0.35%	3
$NRC \rightarrow NE \rightarrow RC$	0.23%	2
$RC \rightarrow NE \rightarrow RC$	0.23%	2
$NRM \rightarrow NE \rightarrow RC$	0.11%	1
$RM \rightarrow NE \rightarrow RC$	0%	0
Total	100%	845

Source: Authors' calculations on the PSID data

Table A.3: Occupational paths towards routine manual occupations (RM)

Occ. Path	**Share**	**N**
$RM \rightarrow RM \rightarrow RM$	68.17%	574
$NRM \rightarrow RM \rightarrow RM$	4.86%	41
$RC \rightarrow RM \rightarrow RM$	4.75%	40
$NRC \rightarrow NRC \rightarrow RM$	3.44%	29
$NRM \rightarrow NRM \rightarrow RM$	3.20%	27
$RM \rightarrow NRC \rightarrow RM$	3.08%	26
$NRC \rightarrow RM \rightarrow RM$	2.73%	23
$RC \rightarrow RC \rightarrow RM$	2.01%	17
$RM \rightarrow NRM \rightarrow RM$	1.42%	12
$RC \rightarrow NRC \rightarrow RM$	1.30%	11
$NE \rightarrow RM \rightarrow RM$	1.06%	9
$RM \rightarrow RC \rightarrow RM$	0.83%	7
$NRM \rightarrow NRC \rightarrow RM$	0.71%	6
$NE \rightarrow NRC \rightarrow RM$	0.59%	5
$NRC \rightarrow NRM \rightarrow RM$	0.35%	3
$NE \rightarrow NRM \rightarrow RM$	0.35%	3
$NRM \rightarrow RC \rightarrow RM$	0.23%	2
$NE \rightarrow RC \rightarrow RM$	0.23%	2
$NRC \rightarrow NE \rightarrow RM$	0.11%	1
$RC \rightarrow NRM \rightarrow RM$	0.11%	1
$RC \rightarrow NE \rightarrow RM$	0.11%	1
$RM \rightarrow NE \rightarrow RM$	0.11%	1
$NRM \rightarrow NE \rightarrow RM$	0.11%	1
$NRC \rightarrow RC \rightarrow RM$	0%	0
$NE \rightarrow NE \rightarrow RM$	0%	0
Total	100%	842

Source: Authors' calculations on the PSID data

Table A.4: Occupational paths towards non-routine manual occupations (NRM)

Occ. Path	**Share**	**N**
$NRM \rightarrow NRM \rightarrow NRM$	37.95%	241
$RM \rightarrow RM \rightarrow NRM$	12.91%	82
$RM \rightarrow NRM \rightarrow NRM$	11.49%	73
$RC \rightarrow NRM \rightarrow NRM$	7.40%	47
$NE \rightarrow NRM \rightarrow NRM$	5.98%	38
$RC \rightarrow RC \rightarrow NRM$	4.88%	31
$NRC \rightarrow NRM \rightarrow NRM$	3.46%	22
$NRC \rightarrow NRC \rightarrow NRM$	2.67%	17
$RC \rightarrow NRC \rightarrow NRM$	1.73%	11
$RM \rightarrow RC \rightarrow NRM$	1.73%	11
$RC \rightarrow RM \rightarrow NRM$	1.57%	10
$NE \rightarrow NE \rightarrow NRM$	1.41%	9
$NRM \rightarrow RC \rightarrow NRM$	1.25%	8
$NRM \rightarrow NRC \rightarrow NRM$	1.10%	7
$NRM \rightarrow RM \rightarrow NRM$	1.10%	7
$NRC \rightarrow RC \rightarrow NRM$	0.78%	5
$RM \rightarrow NRC \rightarrow NRM$	0.62%	4
$NRC \rightarrow RM \rightarrow NRM$	0.47%	3
$RM \rightarrow NE \rightarrow NRM$	0.31%	2
$NE \rightarrow NRC \rightarrow NRM$	0.31%	2
$NE \rightarrow RC \rightarrow NRM$	0.31%	2
$NRC \rightarrow NE \rightarrow NRM$	0.15%	1
$RC \rightarrow NE \rightarrow NRM$	0.15%	1
$NE \rightarrow RM \rightarrow NRM$	0.15%	1
$NRM \rightarrow NE \rightarrow NRM$	0%	0
Total	100%	635

Source: Authors' calculations on the PSID data

Table A.5: Occupational paths towards non-employment (NE)

Occ. Path	**Share**	**N**
$NRC \rightarrow NRC \rightarrow NE$	24.44%	11
$RM \rightarrow RM \rightarrow NE$	17.77%	8
$RM \rightarrow NRC \rightarrow NE$	8.88%	4
$RC \rightarrow RC \rightarrow NE$	6.66%	3
$NRC \rightarrow NE \rightarrow NE$	4.44%	2
$RM \rightarrow NRM \rightarrow NE$	4.44%	2
$NRM \rightarrow RC \rightarrow NE$	4.44%	2
$NRM \rightarrow RM \rightarrow NE$	4.44%	2
$NRM \rightarrow NRM \rightarrow NE$	4.44%	2
$NRC \rightarrow RM \rightarrow NE$	2.22%	1
$NRC \rightarrow NRM \rightarrow NE$	2.22%	1
$RC \rightarrow NRC \rightarrow NE$	2.22%	1
$RC \rightarrow NE \rightarrow NE$	2.22%	1
$RM \rightarrow NE \rightarrow NE$	2.22%	1
$NRM \rightarrow NE \rightarrow NE$	2.22%	1
$NE \rightarrow NRC \rightarrow NE$	2.22%	1
$NE \rightarrow NRM \rightarrow NE$	2.22%	1
$NE \rightarrow NE \rightarrow NE$	2.22%	1
$NRC \rightarrow RC \rightarrow NE$	0%	0
$RC \rightarrow RM \rightarrow NE$	0%	0
$RC \rightarrow NRM \rightarrow NE$	0%	0
$RM \rightarrow RC \rightarrow NE$	0%	0
$NRM \rightarrow NRC \rightarrow NE$	0%	0
$NE \rightarrow RC \rightarrow NE$	0%	0
$NE \rightarrow RM \rightarrow NE$	0%	0
Total	100%	45

Source: Authors' calculations on the PSID data

Table A.6: Occupational paths towards non-routine cognitive occupations (NRC), two age groups

Occ. Path	**Share**	**N**
$NRC \rightarrow NRC$	65.35%	2848
$RC \rightarrow NRC$	18.12%	790
$RM \rightarrow NRC$	8.32%	363
$NRM \rightarrow NRC$	6.49%	283
$NE \rightarrow NRC$	1.69%	74
Total	100%	4358

Source: Authors' calculations on the PSID data

Table A.7: Occupational paths towards routine cognitive occupations (RC), two age groups

Occ. Path	**Share**	**N**
$RC \rightarrow RC$	63.75%	1856
$NRC \rightarrow RC$	13.43%	391
$RM \rightarrow RC$	9.96%	290
$NRM \rightarrow RC$	9.30%	271
$NE \rightarrow RC$	3.53%	103
Total	100%	2911

Source: Authors' calculations on the PSID data

Table A.8: Occupational paths towards routine manual occupations (RM), two age groups

Occ. Path	**Share**	**N**
$NRM \rightarrow RM$	79.75%	2820
$RC \rightarrow RM$	6.92%	245
$NRM \rightarrow RM$	6.79%	240
$NRC \rightarrow RM$	5.14%	182
$NE \rightarrow RM$	1.39%	49
Total	100%	3536

Source: Authors' calculations on the PSID data

Table A.9: Occupational paths towards non-routine manual occupations (NRM), two age groups

Occ. Path	**Share**	**N**
$NRM \rightarrow NRM$	59.24%	1327
$RM \rightarrow NRM$	15.31%	343
$RC \rightarrow NRM$	12.77%	286
$NRC \rightarrow NRM$	7.10%	159
$NE \rightarrow NRM$	5.56%	125
Total	100%	2240

Source: Authors' calculations on the PSID data

Table A.10: Occupational paths towards non-employment (NE), two age groups

Occ. Path	**Share**	**N**
$NRC \rightarrow NE$	26.26%	47
$NRM \rightarrow NE$	22.35%	40
$NE \rightarrow NE$	19.55%	35
$RC \rightarrow NE$	18.99%	34
$RM \rightarrow NE$	12.85%	23
Total	100%	179

Source: Authors' calculations on the PSID data

Appendix B Probability of Joining NRC from Other Occupations

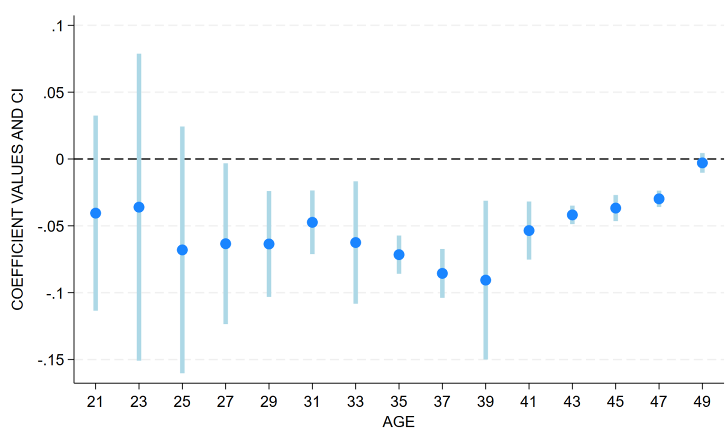

Figure B.1: Correlation between the probability of entering NRC occupations when old and being in NRM occupation when young(er)

Note: Each coefficient is obtained from a separate regression of the form:
$I_{ic}(occ_{old} = NRC) = \psi_0 + \psi_1 I_i(occ_{age} = NRM) + \boldsymbol{\psi_2 cohort_c} + \boldsymbol{\psi_3 year_i} + \boldsymbol{\zeta ind\_contrl_i} + \epsilon_{ic}$.
The base category is the workers in either RC or RM occupations or in non-employment. Blue dots are the point estimates of the ψ_1 coefficient, blue bars are the 95% confidence intervals. For further details, see notes under Figure 4.

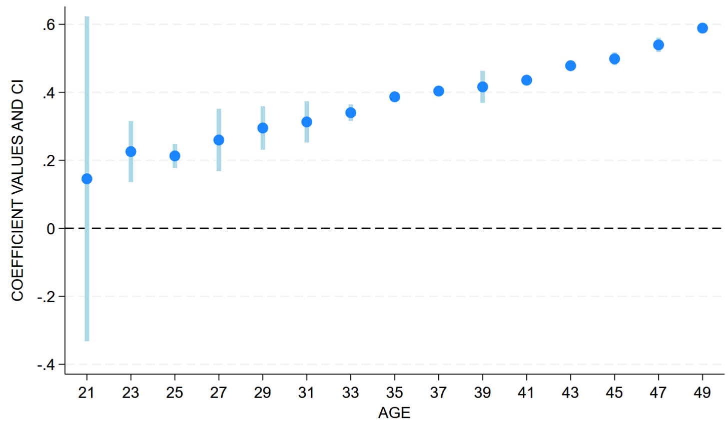

Figure B.2: Correlation between the probability of entering NRC occupations when old and being in NRC occupation when young(er)

Note: Each coefficient is obtained from a separate regression of the form:
$I_{ic}(occ_{old} = NRC) = \psi_0 + \psi_1 I_i(occ_{age} = NRC) + \boldsymbol{\psi_2 cohort_c} + \boldsymbol{\psi_3 year_i} + \boldsymbol{\zeta ind\_contrl_i} + \epsilon_{ic}$.
The base category is the workers in either RC, RM or NRM occupations or in non-employment. Blue dots are the point estimates of the ψ_1 coefficient, blue bars are the 95% confidence intervals. For further details, see notes under Figure 4.

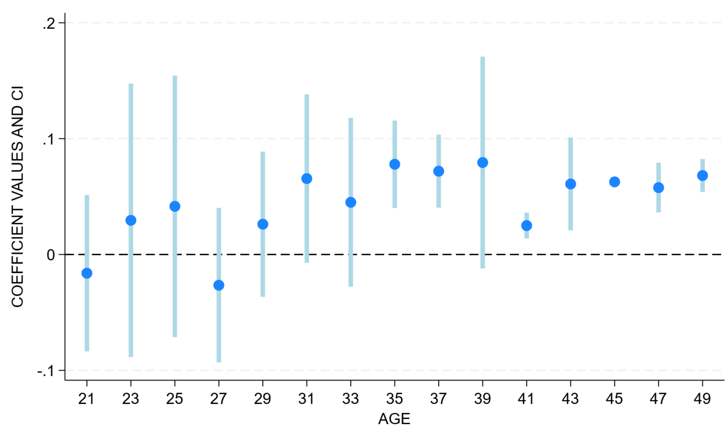

Figure B.3: Correlation between the probability of entering NRC occupations when old and being in NE when young(er)

Note: Each coefficient is obtained from a separate regression of the form:
$I_{ic}(occ_{old} = NRC) = \psi_0 + \psi_1 I_i(occ_{age} = NE) + \boldsymbol{\psi_2 cohort_c} + \boldsymbol{\psi_3 year_i} + \boldsymbol{\zeta ind\_contrl_i} + \epsilon_{ic}$.
The base category is the workers in either RC, RM or NRM occupations. Blue dots are the point estimates of the ψ_1 coefficient, blue bars are the 95% confidence intervals. For further details, see notes under Figure 4.

Appendix C Calibrated Parameter Values

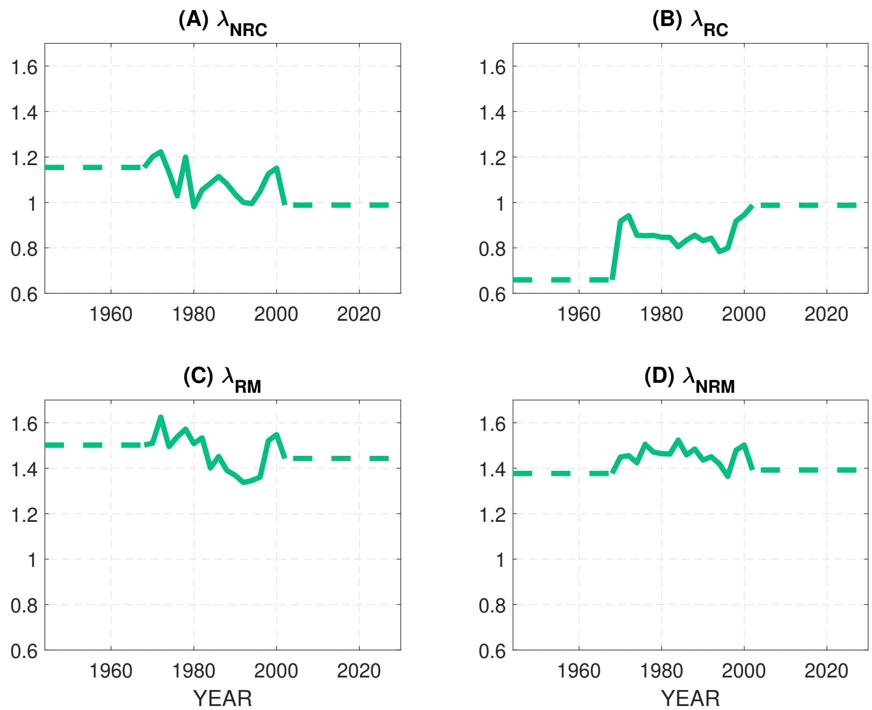

Figure C.1: Calibrated wage rates

Note: The model estimation implies an overall decrease in λ_{NRC} and an increase in λ_{RC} over the studied period. Technically, the vacancy data suggests a significant fall in the employment opportunities in RC occupations and an increase in employment opportunities in NRC occupations. Our model, disciplined by this vacancy data, has to match also the allocations of workers across occupational categories. The corresponding changes in λ_{NRC} and λ_{RC}, to some extent, compensate for the changes in employment opportunities implied by the vacancy data and allow us to match the allocations, as well as the wages across occupational categories.

Intuitively, in our model, λ_j represent the components of earnings in each occupation that is independent of human capital stock. We later on establish that human capital in our model should be interpreted not as general human capital, but rather as a cognition-related set of skills. Therefore, a fall in λ_{NRC}, as well as an increase in λ_{RC}, reflect the changes not directly connected to cognition-related human capital. For instance, a fall in λ_{NRC} may reflect a fall in demand for routine tasks, which are still used in NRC, albeit less intensively than in RM and RC occupations. While an increase in employment opportunities in NRC occupations identifies the changes in demand for the kinds of human capital used most intensively in NRC and RC occupations, λ_j, along with the changes in employment opportunities in other occupations, may reflect changes in the demand and supply of other labor inputs in each occupational category.

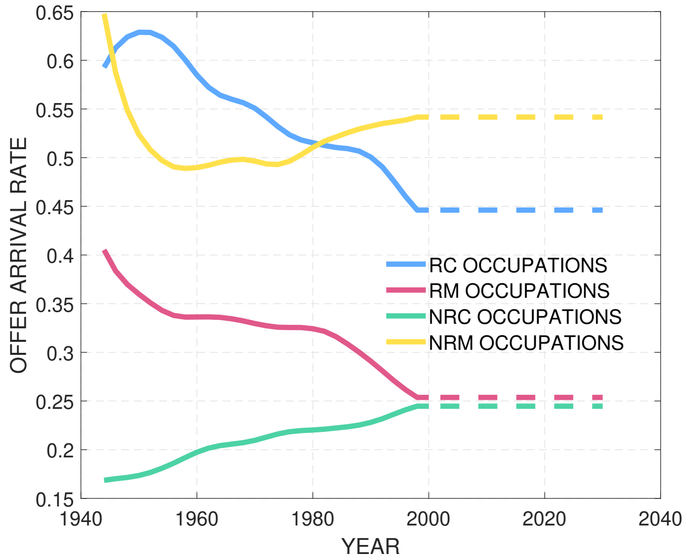

Figure C.2: Job offer arrival rates

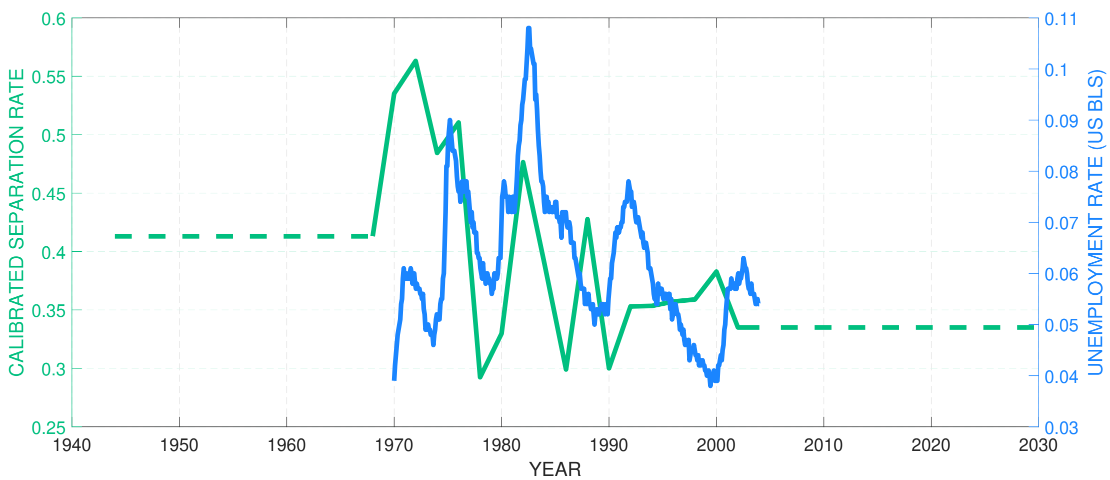

Figure C.3: Separation rate $p_{U,t}$

Note: Superimposed over the calibrated separation rate is the monthly US seasonally adjusted unemployment rate (fred.stlouisfed.org/series/UNRATE). At least until the mid 1980s, there is a large degree of comovement between the model's separation rate and the data-based unemployment rate.

Appendix D Additional Counterfactual Results

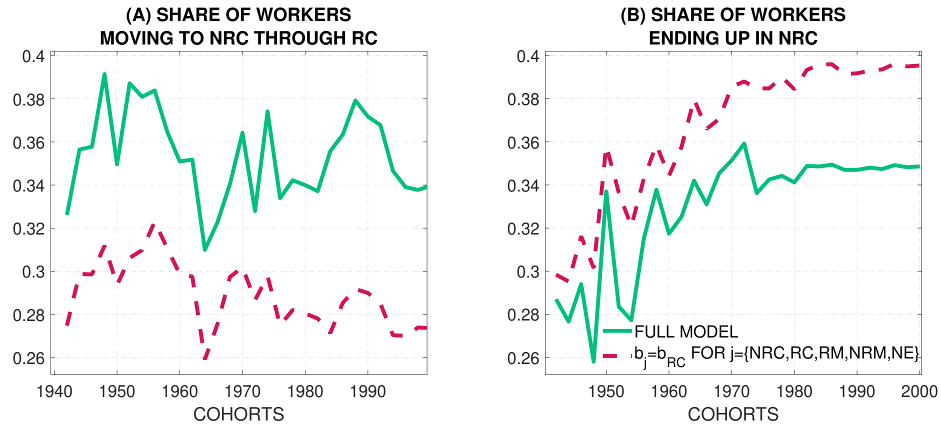

Figure D.1: Workers' transitions to NRC occupations by older age in full model and in the model with same human capital accumulation in all occupations

Note: The counterfactual model is simulated under the human capital accumulation in all occupations set equal to human capital accumulation in RC (b_{RC}). All other parameters in the counterfactual model are the same as in the full model.

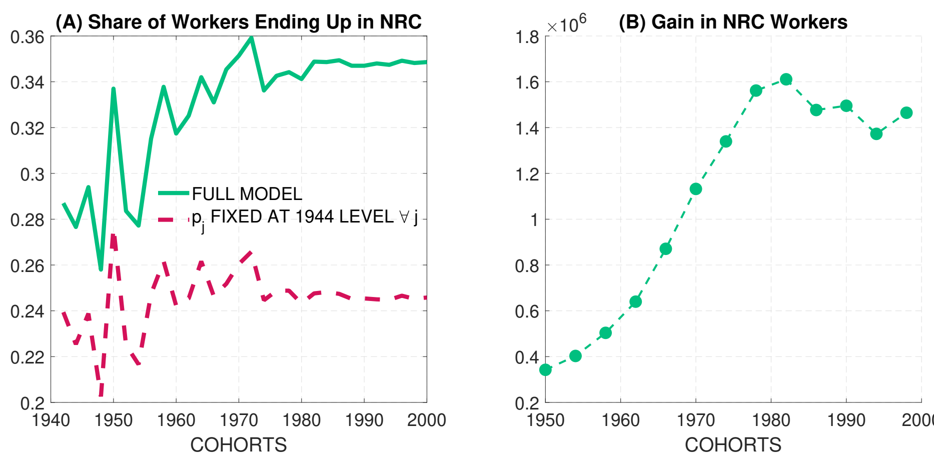

Figure D.2: Workers' transitions to NRC occupations by older age in full model and in the model with all arrival rates fixed at 1944 level

Note: For panel (A), all parameters in the counterfactual model are the same as in the full model, besides the job offer arrival rates from all occupations that in the counterfactual model are fixed at their respective year 1944 levels. For panel (B), the gain of workers is calculated using the youngest 20-24 y.o. civilian labor force (data from fred.stlouisfed.org/series/LNS11000036) in each year and taking the share of it implied by the percentage point difference between the full model and the counterfactual model from panel (A).

Abstrakt

Které profesní dráhy vedou pracovníky k vysoce kvalifikovaným nerutinním kognitivním povoláním? Na základě dat z PSID ukazujeme, že pro značnou část pracovníků vede kariérní cesta k nerutinním kognitivním povoláním přes rutinní povolání se střední kvalifikací, přičemž většina z nich prochází podskupinou rutinních kognitivních povolání. Poté tvrdíme, že pokles zaměstnanosti v rutinních kognitivních povoláních v důsledku technologických změn vychýlených vůči rutinním povoláním může negativně ovlivnit šance mladších kohort na vstup do vysoce kvalifikovaných povolání. K ověření této hypotézy vytváříme strukturální model volby povolání, který endogenně generuje realistické kariérní dráhy, a odhadujeme jej na základě dat z PSID a údajů z pracovních inzerátů tří hlavních amerických burz práce, které pokrývají období od roku 1940 do roku 2000. Naše odhady naznačují, že v průměru 6 % pracovníků, kteří končí v nerutinních kognitivních povoláních, využívá rutinní kognitivní povolání jako odrazový můstek, který jim umožňuje udržovat a akumulovat lidský kapitál a zkušenosti důležité pro pozdější zaměstnání ve vysoce kvalifikovaných povoláních. Pokles pracovních příležitostí v rutinních kognitivních povoláních v období nejintenzivnějších technologických změn vychýlených vůči rutinním povoláním vedl ke ztrátě nejméně 1,37 milionu vysoce kvalifikovaných pracovníků, kteří uvízli v méně kvalifikovaných povoláních.

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