CHARLES UNIVERSITY
FACULTY OF SOCIAL SCIENCES
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Dissertation Thesis

2024 **Daniil Kashkarov**

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Essays on Human Capital, Inequality and Technological Change

Dissertation Thesis

Prague 2024

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Year of defense: 2024

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References

Kashkarov, D. (2024). *Essays on Human Capital, Inequality and Technological Change.* Dissertation thesis, Charles University, Faculty of Social Sciences, Center for Economic Research and Graduate Education (CERGE-EI).

Abstract

In this thesis, I study the adaptation of workers to labor market disruptions, with emphasis on adaptation to technological change, through the lens of structural life-cycle models of skill investment and occupational choice. In the first chapter, I use a life-cycle model of human capital investment and occupational choice to link the adaptive capacity of workers with different learning abilities to earnings inequality that arises in the process of routine-biased technological change (RBTC). Estimating the model on NLSY79 and CPS data, I establish that the responses of workers with higher learning ability in routine occupations, who adapt to RBTC by accumulating additional human capital and switch to non-routine cognitive occupations, significantly dampen an RBTC-induced increase in the non-routine cognitive wage premium.

The second chapter focuses on how generations of workers adapt to routine-biased technological change by altering their career paths. We develop a model which endogenously generates realistic career paths across routine and non-routine occupations over worker' lifetimes and estimate it using PSID data and job ad data from three major US outlets covering the period from 1940 to 2000. We show that, in the course of RBTC, the disappearance of a subset of routine occupations used as stepping stones can decrease the chances of workers from younger cohorts to progress towards high-skilled non-routine cognitive occupations later in the life cycle. While a significant share of younger workers adapts by altering their career paths towards the high-skilled occupations, these alternative paths are often associated with human capital depreciation affecting the wage distribution for younger cohorts of non-routine cognitive workers.

In the third chapter, I extend the economic model of workers' decision-making to account for the characteristics of environment that are considered the most important in adaptation theory in biology and ecology — sciences that study and predict adaptation in a wide variety of contexts for some of the most diverse entities in the universe. I then estimate the economic model informed by adaptation theory in biology and ecology on the NLSY79

and O*NET data and use it to quantitatively evaluate the adaptation predictions delivered by biology and ecology in the context of labor markets. The universality of the results delivered by many decades of adaptation research in biology and ecology allows me to analyze the adaptive responses of workers across different contexts within a single framework, to predict the consequences of major labor market disruptions, such as automation, the introduction of AI, and climate change.

Abstrakt

V této práci studuji adaptaci pracovníků na narušení trhu práce s důrazem na adaptaci na technologické změny, a to z pohledu strukturálních modelů životního cyklu investic do dovedností a volby povolání. V první kapitole používám model životního cyklu investic do lidského kapitálu a volby povolání k propojení adaptační schopnosti pracovníků s různými schopnostmi učení s nerovností ve výdělcích, která vzniká v procesu rutinní technologické změny (RBTC). Na základě odhadu modelu na datech NLSY79 a CPS zjišťuji, že reakce pracovníků s vyššími schopnostmi učení v rutinních profesích, kteří se přizpůsobují RBTC akumulací dodatečného lidského kapitálu a přecházejí do nerutinních kognitivních profesí, významně tlumí nárůst mzdové prémie za nerutinní kognitivní profese vyvolaný RBTC.

Druhá kapitola se zaměřuje na to, jak se generace pracovníků přizpůsobují rutinním technologickým změnám tím, že mění své kariérní dráhy. Vyvíjíme model, který endogenně generuje realistické kariérní dráhy v rutinních a nerutinních profesích v průběhu života pracovníka, a odhadujeme jej na základě údajů PSID a údajů z inzerátů na pracovní místa ze tří hlavních amerických zprostředkovatelů inzerce, které pokrývají období od roku 1940 do roku 2000. Ukazujeme, že v průběhu RBTC může zánik části rutinních povolání používaných jako odrazový můstek snížit šance pracovníků z mladších kohort na postup k vysoce kvalifikovaným nerutinním kognitivním povoláním v pozdější fázi životního cyklu. Značná část mladších pracovníků se sice přizpůsobí změnou své profesní dráhy směrem k vysoce kvalifikovaným povoláním, ale tyto alternativní dráhy jsou často spojeny se znehodnocením lidského kapitálu, které ovlivňuje rozdělení mezd mladších kohort nerutinních kognitivních pracovníků.

Ve třetí kapitole rozšiřuji ekonomický model rozhodování pracovníků tak, aby zohledňoval vlastnosti prostředí, které jsou považovány za nejdůležitější v teorii adaptace v biologii a ekologii — vědách, které studují a předpovídají adaptaci v nejrůznějších souvislostech pro některé z nejvíce rozdílných entit ve vesmíru. Ekonomický model založený na teorii adaptace v biologii a ekologii pak odhaduji na datech NLSY79 a O*NET a používám jej ke kvantitativnímu vyhodnocení předpovědí adaptace, které poskytují biologie a ekologie v kontextu trhů práce. Univerzálnost výsledků, které přináší mnoho desetiletí výzkumu adaptace v biologii a ekologii, mi umožňuje analyzovat adaptační reakce pracovníků v různých kontextech v jednom rámci a předpovídat důsledky velkých narušení trhu práce, jako je automatizace, zavádění umělé inteligence a změna klimatu.

Keywords

Human capital, life-cycle modelling, routine-biased technological change, occupational choice, career paths, multidimensional skills, adaptation of workers, labor market environment

Klíčová slova

Lidský kapitál, modelování životního cyklu, rutinní technologické změny, volba povolání, kariérní dráhy, vícerozměrné dovednosti, adaptace pracovníků, prostředí trhu práce

Length of the work:

271,296 characters with spaces, without abstract and appendices

Declaration

1. I hereby declare that I have compiled this thesis using the listed literature and resources only.
2. I hereby declare that my thesis has not been used to gain any other academic title.
3. I fully agree to my work being used for study and scientific purposes.

In Prague on 09.05.2024. Daniil Kashkarov

Acknowledgements

Firstly, I would like to express my sincere gratitude to my supervisors at CERGE-EI — Marek Kapička and Ctirad Slavík — for their constructive feedback, invaluable advice, encouragement, and responsiveness throughout my PhD studies.

I especially thank Aleh Tsyvinski, my supervisor at Yale, for inspiring me and shaping my research ideas, for providing me with plenty of opportunities to improve and work on myself, and for helping me to find my unique research path.

Many thanks to other members of my Dissertation Committee — Sergey Slobodyan and Veronika Selezneva — for all support and advice that I received from them at different stages of my PhD studies

My sincere appreciation goes to the CERGE-EI Academic Skills Center, particularly Deborah Nováková, Gray Krueger, and Andrea Downing, for their professional editing of the text and valuable feedback on my presentations throughout my academic journey. Additionally, I extend my appreciation to SAO for their assistance and support.

I would like to thank my parents and my brother for being the fundamental driving force behind my academic endeavours. I am also extremely grateful to my partner for being a source of inspiration and energy in the most difficult years of my PhD.

I gratefuly acknowledge financial support from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 870245; the Grant Agency of Charles University projects No. 21812 and No. 144822; and NPO "Systemic Risk Institute" number LX22NPO5101, funded by European Union — Next Generation EU (Ministry of Education, Youth and Sports, NPO: EXCELES).

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Introduction

The focus of this thesis is on the adaptation of workers to current and prospective labor market disruptions, with a particular emphasis on workers' adaptation to technological change. The thesis progresses from development of classical life cycle models of workers' decision making, featuring skill accumulation and occupational choice, to the economic model informed by adaptation theory in biology and ecology — sciences that, for at least two centuries, have been studying and successfully predicting the adaptation of the most diverse entities in the universe across a broad variety of contexts.

In the first chapter, I develop a life-cycle model of human capital investment and occupational choice to link the adaptive capacity of workers with different learning abilities to the earnings inequality that arises in the process of routine-biased technological change (RBTC). The model is calibrated to National Longitudinal Survey of Youth 1979 (NLSY79) data, using the price series for human capital in high-skilled non-routine cognitive occupations and in middle-skilled routine occupations estimated from cross-sectional Current Population Survey (CPS) data.

Running a series of counterfactual exercises, I establish that, for the NLSY79 cohorts, increasing prices of human capital in non-routine cognitive occupations and decreasing prices of human capital in routine occupations in the course of RBTC, together with the induced human capital responses, contribute up to 28.6% to the non-routine cognitive wage premium. The adaptive responses of workers with higher learning ability from routine occupations, who are able to accumulate additional human capital and switch to non-routine cognitive occupations in the face of RBTC, result in the abstract wage premium being 35.5 percentage points lower than it would be in the absence of adaptive human capital responses.

The second chapter, co-authored with Valentin Artemev (CERGE-EI), studies how generations of workers adapt to routine-biased technological change by altering their career paths. Specifically, we pose a question: which career paths lead workers towards high-skilled non-routine cognitive occupations? Using Panel Study of Income Dynamics (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 opportunities in routine cognitive occupations due to RBTC 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. A significant share of workers, however, were able to adapt to shrinking employment opportunities in routine cognitive occupations and reached non-routine cognitive occupations through routine manual and non-routine manual occupations. The depreciation of human capital associated with following these alternative career paths results in a wage loss once workers reach non-routine cognitive occupations. The wage loss associated with lower human capital is the most pronounced in the middle of the wage distribution of the non-routine cognitive workers.

In the third chapter, I develop an economic model in which workers with different stocks of cognitive, manual, and interpersonal skill make skill investment decisions and choose jobs characterized by different requirements for each of the skills. I extend this model to account for the characteristics of environment considered to be the most important in adaptation theory in biology and ecology. Two key environmental characteristics, timescale of environment variation and predictability (or control) over the environment, allow biologists and ecologists to put structure on the analysis of adaptive responses across a broad variety of contexts. The distinct variable environments are represented through environmental signatures — the combinations of the timescale of environment variation and control over the environment. Following the approach towards the characterization of changing environments in biology and ecology, adapting the concept of environmental signatures to economic context, I use these two variables to characterize changing labor market environments.

In the context of the model developed in this chapter, the timescale of environment variation is the frequency with which workers are changing their jobs and the associated skill requirements. Workers in seasonal jobs, e.g., in the tourist-oriented hospitality sector or seasonal construction, are facing shorter timescales, while workers with long-term contracts, e.g., tenured professors or engineers, are facing longer timescales. Control over the job choice is the precision with which workers can choose their future jobs and the associated skill requirements. Among other things, control over the job choice, in a reduced form, may represent efficiency of employer-employee matching, labor market thickness, and rapid changes in demand for skills in a particular industry, as well as in the whole economy.

I use the model, which I extend to account for difference in the timescales of environment variation and control over the job choice across workers, to quantitatively evaluate the predictions of adaptation theory from modern biology and ecology in the context of changing labor market environments. Key predictions are: 1. The environmental signatures define the modes of adaptation; 2. Transitions between environmental signatures are associated with tipping points; 3. Environment change forges adaptive capacity, with bimodality in adaptive responses.

Estimating the model on the NLSY79 and O*NET data and simulating workers' adaptive outcomes for different labor market environments, I find that the first prediction holds for cognitive skill, with distinct modes of adaptation, in principle, similar to those studied in biology and ecology. At the same time, manual and interpersonal skills do not produce distinct response modes and are either changing continuously or are fixed across environments. Transitions between the adaptive modes of cognitive skill are associated with substantial losses in lifetime consumption and higher unemployment risks and represent the adaptation tipping points. Further, I establish that the adaptive capacity of workers is forged at the highest levels of environment variability. In the same environments, the distribution of the cognitive skill of workers becomes bimodal, whereby the mass of intermediate cognitive skill workers decreases and the mass of workers with lower and higher cognitive skills increases.

I further discuss the sources of differences in the environments faced by workers. Different environments can be represented by industries, occupational categories, labor markets for different educational groups, as well as by the local labor markets, e.g., at the commuting zone level. Representing occupational categories as distinct labor market environments, I map them into adaptive response mode regions of cognitive skill and discuss the adaptive capacity of workers from different occupations in the face of automation, introduction of AI, and climate change. I relate the bimodality of cognitive skill distribution in the environments characterized by high variability of cognitive skill requirements with the observed labor market polarization.

The third chapter of this thesis is my first step towards the development of a new research direction, where predictions, insights, and methods from modern biology and ecology will be introduced to better understand and predict the economic processes.

Chapter 1

RBTC and Human Capital: Accounting for Individual-Level Responses

1.1 Introduction

In the last two decades, the economic literature studying the effects of routine-biased technological change (RBTC) on general production patterns has witnessed rapid development (Acemoglu & Autor, 2011a; Sachs & Kotlikoff, 2012; Autor & Dorn, 2013a; Sachs et al., 2015; Acemoglu & Restrepo, 2018). While current studies mostly attempt to identify the direct consequences of RBTC, including reallocations of the labour force (Autor et al., 2006b; Goos & Manning, 2007a; Autor & Dorn, 2013a) and changes in wage schedules (Acemoglu & Restrepo, 2020), less attention has been dedicated to the consequences of the responses of individual workers to the (dis)incentives created by this kind of technological change[1]. In particular, the possibility to adjust human capital in response to RBTC gives rise to several channels through which the distribution of earnings can be affected.

The capital-skill complementarity relationship (Krusell et al., 2000; Autor et al., 2003a) implies that one way for workers to mitigate the possible impacts of RBTC at the individual level is to accumulate human capital through education or on-the-job training, which allows them to supply more sophisticated types of labour. Individuals possessing

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

high levels of human capital absorb the benefits created by technological change in high-skill occupations. In contrast, individuals with lower levels of human capital who are unable to accumulate it in sufficient amounts are expected to bear the losses associated with the replacement of middle-skill occupations in the course of RBTC. Autor & Dorn (2009a) show that workers who have a college degree, and thus possess a higher stock of human capital, are able to relocate from middle- to high-skill occupations. Lower human capital agents are more likely to relocate to low-skill occupations, non-employment or to remain in middle-skill occupations that are gradually disappearing (Autor & Dorn, 2009a; Cortes, 2016a; Cortes et al., 2017a).

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

A cross-country analysis conducted by (PricewaterhouseCoopers, 2018), which is in line with the results obtained by Frey & Osborne (2017) and Acemoglu & Restrepo (2020), suggests that the risk of replacement by technology is the most pronounced for the individuals with low levels of education. These are workers often employed in occupations classified as *routine*, e.g., manufacturing, administration and support services. Routine occupations are characterized by a set of well-defined, often repetitive, tasks that can be to a high extent automated through computerization and robotization. This is a group of occupations responsible for a decrease in employment in middle-skilled occupations (Acemoglu & Autor, 2011a). Cortes (2016a) demonstrates on the PSID data the presence of ability-based selection out of the routine occupations, with lower ability agents having lower chances to join *abstract* occupations. Abstract occupations, e.g., engineers or managers, require non-standard thinking, perpetual learning, adaptability and high level of skill/human capital. This group of occupations is considered to be complemented by technology and has experienced a dramatic rise in wages over the last decades (Acemoglu & Autor, 2011a).

In this paper I acknowledge the fact that RBTC creates incentives for individuals to enter the abstract occupations in order to benefit from the rising returns on working in them. This kind of individual response is akin to an increase in college attainment in the context of traditional skill-biased technological change (among recent contributions are Kong et al. (2018), and Donovan & Herrington (2019)). For the individuals employed in abstract occupations, an increase in the productivity of human capital motivates them to further augment their personal human capital stock. At the same time, individuals with low learning ability and/or stock of human capital find it relatively more costly to accumulate human capital and can be constrained in their capacity to enter abstract occupations and benefit from RBTC. With such individuals having lower opportunities to enter abstract occupations, a situation occurs when the benefits from the technological change are predominantly accrued to the individuals with higher ability and human capital, while those with less favorable conditions remain constrained in their mobility towards abstract occupations. This uneven allocation of the benefits created by RBTC may further amplify the mechanism driven by heterogeneity in ability and human capital described by Huggett et al. (2006) and can contribute to a rise in the dispersion of earnings over the working life cycle.

The aim of this study is to test the contribution of a change in prices for human capital in routine and abstract occupations, and the resulting individual human capital responses over the working life cycle, to the earnings inequality arising from the process of RBTC. To this end, I develop a life-cycle model of human capital investment and occupational choice. The workers in the model are heterogeneous in their routine occupation productivity, initial stock of human capital in abstract occupation, and learning ability. Observing the price changes for human capital in abstract and routine occupations, workers make occupational choices and decide on the amount of investment into human capital in abstract occupations. The decisions are based on the workers' productivities in routine and abstract occupations and their learning ability, which captures the speed with which human capital in abstract occupations can be accumulated.

I calibrate the model to the NLSY79 data, using the AFQT scores as the measures of ability. The data analysis suggests that the ability is predictive of individuals' capacity to adjust to RBTC. While agents with lower learning ability, over-represented in routine occupations, experience limited opportunities for upward mobility towards abstract occupations, highly-able workers in abstract occupations are potentially responding to a rise in prices for human capital in abstract occupations by augmenting their own stock of human capital.

To estimate the changes in human capital prices over the lifetime of the NLSY79 cohorts, I apply the "flat spot" approach (Bowlus & Robinson, 2012) to the abstract and routine occupational categories in the CPS data. This approach allows me to separate the changes in prices of human capital in abstract and routine occupations from the changes in their respective stocks. The estimates of the price series suggest that the prices for human capital in abstract occupations have increased by more than 18 per cent from 1976 to 2019, while for human capital in routine occupations the prices decreased by 23 per cent over the same period of time. This is in contrast with Bowlus & Robinson (2012), who show a large degree of comovement between the human capital types approximated by the educational categories. These differences in estimates speak for the relevance of the task-based approach (Acemoglu & Autor, 2011a) in the analysis of wage changes happening over the recent decades.

The life-cycle model of human capital investment and occupational choice calibrated to the NLSY79 data with the human capital prices estimated from the CPS data reproduces the life-cycle profiles of abstract wage premium and variance of log-earnings, as well as the ability distributions in abstract occupations at the age of 25 and 50. The model also reproduces the abstract-to-routine and routine-to-abstract occupational mobility over the life cycle of the NLSY79 cohorts. I use the calibrated model to quantify the effects of individual human capital responses to earnings inequality.

I first fix the prices for human capital at their 1979 level. The difference between the life-cycle profiles in the model with fixed prices and the same profiles in the full model shows the overall effect of changes in the prices on earnings inequality. Increasing prices of human capital in abstract occupations and decreasing prices of human capital in routine occupations together with the induced human capital responses contribute up to 10.8 per cent to the variance of log-earnings and up to 28.6 per cent to the abstract wage premium. The contribution of the price changes is increasing with age. Further counterfactual exercises show that the variance of log-earnings is largely driven by the initial conditions, with the changes in human capital prices over the lifetime of the NLSY79 cohorts playing a rather modest role.

To isolate the effect of human capital responses on earnings inequality, I run a version of the model where the prices for human capital are changing as estimated from the CPS data, but with the workers choosing occupations and investing into human capital as if the prices are fixed on 1979 level. The difference between this "no-response" version of the model and the full model suggests an inequality dampening effect of human capital responses. Although a significant part of the routine workers is never able to join abstract occupations, the responses of those who manage to make a routine-to-abstract occupational switch result in the abstract wage premium being 35.5 percentage point lower than it would be in the absence of individual human capital responses.

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

The rest of the paper proceeds as follows. Section 1.2 describes the main source of data used in this paper – NLSY79. It provides the reader with the micro evidence suggesting the presence of ability-based selection into abstract and routine occupations that persists over the working life cycle. Section 1.3 develops a dynamic life-cycle model. Section 1.4 uses cross-sectional CPS data to estimate the price series for human capital in routine and abstract occupations. Section 1.5 describes the calibration of the model developed in Section 1.3 and discusses its fit to the data. Section 1.6 runs the counterfactual exercises that are used to establish the effect of a change in prices of human capital in abstract and routine occupations on the evolution of variance of log-earnings and the abstract wage premium, over the working life cycle of the NLSY79 cohorts. Section 1.7 concludes.

1.2 Data and Micro Evidence

1.2.1 NLSY79 Data and Sample Restrictions

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

This paper uses males aged 23-57 from the cross-sectional sample of the NLSY79[3]. The lower bound for the age restrictions is motivated by the fact that for males younger than 23 the occupational data is either largely missing or shows the signs of miscoding. For the upper bound, as the set of NLSY79 cohorts is approaching retirement age, the number of observations starts to fall rapidly, yielding imprecise estimates of the earnings statistics after the age of 57. Further, the sample is restricted to the observations with

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

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

yearly working hours between 260 and 5820 for those under 30, and between 520 (a quarter of full-time work hours) and 5820 for those over 30. Individuals under 30 are required to earn at least $1000 a year, while those over 30 are required to earn at least $1500. All earnings are in 1979 prices. Restrictions on hours and earnings are associated with the specification of the model used in this paper, in which there only two forms of time usage: either working or learning (accumulating human capital). For workers under 30, hours and earnings restrictions are lowered to allow for the possibility of a part-time job while studying.

Table 1.A1 in the appendix shows the sizes of the restricted sample of NLSY79 males and the respective shares of broad occupational categories across different age groups. A sample satisfying all the restrictions consists of 32,476 occupational observations for 3,003 individuals. There are a total of 12,016 and 17,537 occupational observations in abstract and routine occupations, respectively. As mentioned above, the share of service occupations is relatively small and does not exhibit any clear upward or downward movement over the working life cycle of the NLSY79 cohorts[4]. In contrast, the share of abstract workers gradually increases over the working life cycle as the workers from routine occupations switch to abstract occupations.

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

1.2.2 Ability and Relocation of Labour between Routine and Abstract Occupations

Individuals from the NLSY79 data were entering their prime age and were already actively participating on the labour markets in between the 1980s and the beginning of the 2000s. This period in US history was marked by a declining employment share

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

for routine occupations and an increasing wage premium for non-routine (abstract and service) occupations (Autor & Dorn, 2013a; Eden & Gaggl, 2018a). These labour market trends are commonly attributed to the onset of RBTC and were accompanied by rapidly-falling costs of performing standardized computations (Nordhaus, 2007) and by a growing ICT capital income share (Eden & Gaggl, 2018a). Therefore, while keeping track of a relatively narrow set of cohorts, the NLSY79 includes observations for individuals who were making their decisions in an economy transitioning towards lower use of routine labour. In other words, the NLSY79 cohorts were among those exposed to the initial effects of RBTC and had to behave in accordance with the rapidly changing labour market conditions.

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

Figure 1.1 shows the distributions of individuals by ability quartiles in abstract and routine occupations, as measured by their AFQT scores. The distributions are calculated for individuals aged 25 and 50. By the age of 25 the majority of young males have already entered the labor market (occupational codes are available for a large share of the sample), while by the age of 50 the mobility across occupations falls significantly in the NLSY79 data, and the occupational distributions become virtually constant. In other words, occupational distributions as of age 25 and 50 are chosen to approximate the sorting into abstract and routine occupations at the beginning and end of the working life cycle.

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

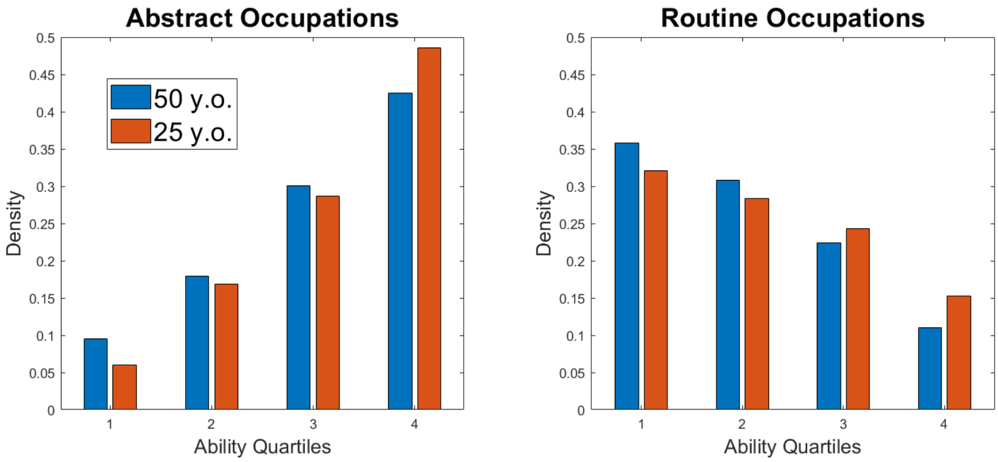

Figure 1.1: Occupational Distributions by Ability Quartiles

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

A high share of low ability individuals in routine occupations at the beginning and end of the working life cycle suggests that, when exposed to the effects of RBTC, a significant share of routine workers might be incapable of joining abstract occupations. In the course of the working life cycle, the AFQT-based measure of ability predicts the probability of routine-to-abstract (RA) and abstract-to-routine (AR) occupational switches. The left panel of Figure 1.2 shows that the probability of switching from a routine to abstract occupation (calculated as the probability of changing occupation between period t and $t+2$) is larger for individuals with higher ability. This pattern holds true for different age intervals (25-34, 35-44 and 45-54), with the overall probability of RA switches falling over age. The right panel of Figure 1.2 shows the probabilities of AR switches. Less able agents in abstract occupations are more likely to switch to routine occupations, than their more able counterparts. In general, Figure 1.2 suggests that during RBTC, as conditions in routine occupations deteriorate, more-able agents in routine occupations would demonstrate a higher capacity to adjust to the changes on the labor market by switching to abstract occupations. For lower ability agents there is less opportunity for adjustment and, even if they manage to enter the abstract occupations, there are higher chances for them falling back into routine occupations.

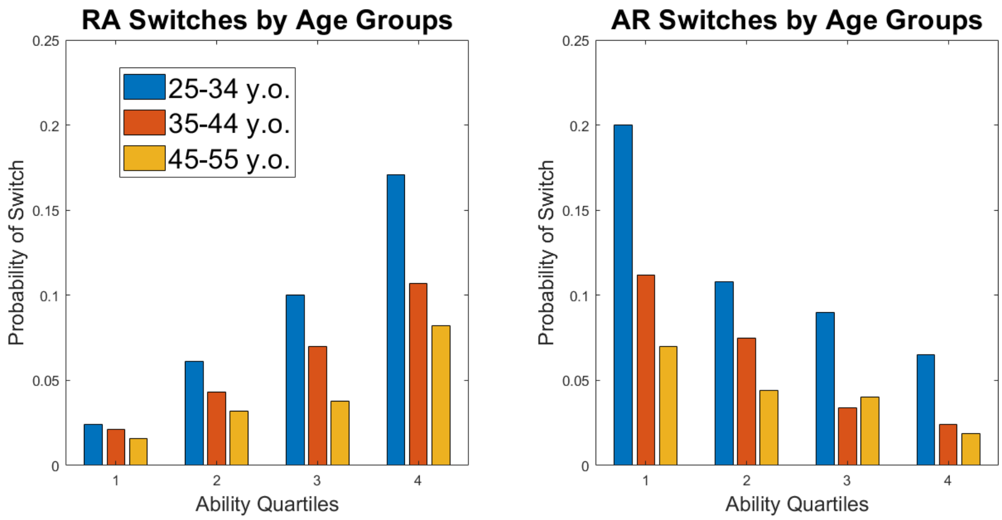

Figure 1.2: Occupational Switch Probabilities by Ability Quartiles

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

Table 1.1 sheds some light on the long-run occupational paths in the NLSY79 data by comparing the workers who switch from routine occupations between years t and $t+2$ to those who remain in routine occupations over the same period. For each ability quartile, the table shows the shares of workers by the occupations in which they are observed in $t+10$, conditional on either switching or staying in a routine occupation in year $t+2$. With a rise in the workers' ability, the share who follow the RAA path, i.e., starting in a routine occupation in t, switching to an abstract occupation by $t+2$ and ending up in an abstract occupation in $t+10$, increases relative to the share who follow the RAR path (switching to abstract by $t+2$ and falling back to routine by $t+10$). This is in line with Figure 1.2, which shows the higher probabilities of falling back to routine occupations for low ability routine workers who managed to switch to abstract occupations at some point over the working life cycle.

Mobility across routine and abstract occupations over the working life cycle contributes to the differences in ability-based selection between the initial and final occupational distributions. As can be seen from Figure 1.1, the initial distribution for abstract occupations exhibits steeper ability-based selection than the final one. The opposite holds true for routine occupations. In addition to the selection out of the sample, these differences in the degrees of ability-based selection at the beginning and towards the end of the working life cycle are largely driven by the net occupational mobility from routine occupations. Table 1.1 shows that the majority of those who switch their occupation in the long run, are following either RAA or RRA paths. Such occupational paths are observed across all ability quartiles and a share of individuals who upgrade from routine to abstract occupations throughout the working life cycle dampens the selection in the final ability-based distribution in abstract occupations. On the other hand, the fact that the probability of occupational upgrading is rising in ability, increases the share of lower-ability agents in routine occupations towards the end of the working life cycle.

Table 1.1: Occupational Paths for Routine Workers (by Ability Quartiles)

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

Note: R-routine occupation, A-abstract occupation, S-service occupation. First three columns show the periods in which observations of occupational category are taken for each individual: in a current year, in two years and in 10 years. The last four columns show the fractions of workers from different ability quartiles following a particular occupational path. Probabilities of the occupational paths are calculated in the same manner as the probabilities of switching categories for Figure 1.2. Here, the observations in service occupations are also included.

Table 1.A2 in the Appendix also shows that the reverse pattern for the long-run occupational mobility holds true for abstract occupations: the probability of being observed in a routine occupation in 10 years is falling with ability. The mobility from abstract occupations partially offsets the selection effect of mobility from routine occupations on

the final occupational distributions. However, as can be seen from Table 1.A1, the share of abstract workers in all periods is lower than that of routine workers, making the flow from abstract occupations smaller in absolute terms than that from routine occupations.

The occupational paths of the RAA or RRA type generally represent cases of occupational upgrading. Table 1.A3 in the appendix compares the labor income at the end of the occupational path for those who changed occupation with those who remained in the occupational category in which they started the path. As follows from Panel 1, the labor income 10 years after being observed in a routine occupation is higher for those individuals who follow the RRA and RAA paths, than for those who remain in a routine occupation. This holds true across all the ability quartiles. In this context, the RAA and RRA paths can be rationalized by a gradual accumulation of human capital necessary for employment in abstract occupations. Such occupational path is considerably more likely for individuals with higher ability. At the same time, as suggested by Panel 2 of Table 1.A3, individuals switching from abstract occupations and following the AAR and ARR occupational paths find themselves earning less than those staying in A occupations. This occupational downgrading is more likely for less-able individuals.

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

1.3 Model of Human Capital Investment and Occupational Choice

For the analysis of the effects of RBTC on individual decisions about the accumulation of human capital I introduce two types of labour, routine and abstract, into a human capital model developed in the spirit of Huggett et al. (2006; 2011). Optimization problem 1.1 defines the decisions made by the agents in the model. Agents live for J periods and maximize the present value of their consumption. In each period, the labor income y_j is divided between consumption c_j and monetary investment into human capital in abstract occupation d_j. Labor income in each occupation is defined as the product of the price of human capital $P_{k,t}$ (price per efficiency unit of labor), the stock of human capital $h_{k,j}$, and working time l_j. Agents allocate a unit endowment of time in each life-cycle period j between working in either an abstract or routine occupation and learning time n_j. In each period, the stocks of human capital in abstract and routine occupations are hit by the idosyncratic zero-mean shocks $z_{A,j}$ and $z_{R,j}$.

$$\max_{\{c_j, occ_j, l_j, n_j, d_j, h_{j+1}\}_{j=1}^{J}} \mathbb{E}_0 \left[\sum_{j=1}^{J} \beta^{j-1} c_j \right] \tag{1.1}$$

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

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

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

Changes in prices for human capital alter the decisions of agents regarding the amount and type of labour supplied. Agents choose to supply abstract or routine labour based on their comparative advantage, in the tradition of Roy (1951). Inequality 1.2 must hold for the agent to supply abstract labour. Abstracting from the human capital shocks, price-adjusted productivity in a routine occupation should be lower than the productivity in an abstract occupation for the agent to choose an abstract occupation. Changes in relative prices affect the decisions of agents by: (1) increasing/lowering the threshold for an occupational switch defined by Inequality 1.2; (2) changing the returns to monetary and time investment into human capital in an abstract occupation.

$$h_{A,j} \geq \frac{P_{R,t}}{P_{A,t}} \frac{exp(z_{R,j})}{exp(z_{A,j})} h_{R,j} \tag{1.2}$$

Equations 1.3 and 1.4 define the laws of motion for the stocks of human capital in abstract and routine occupations. Similarly to Huggett et al. (2006; 2011), individual agents start their J-period lives with the draws of initial human capital in abstract occupation $h_{A,1}$ and ability a, differing across the agents. Human capital accumulation in abstract occupations is of a Ben-Porath (1967) type. As follows from Equation 1.3, to extend the stock of human capital in an abstract occupation, the current stock of human capital in abstract occupation $h_{A,j}$ is combined with learning time n_j and a share of consumption good d_j in a human capital production function of a Cobb-Douglas form with elasticities α_1 and α_2. Ability a affects the slope of the human capital production function, i.e., the speed with which human capital in abstract occupations can be accumulated.

From Equation 1.4, human capital in routine occupations is set to follow function $f(j)$, which captures the evolution of earnings over the working life cycle of a routine worker and can be regarded as the age premium in the routine occupation. An additional initial condition η is associated with the productivity in the routine occupation, shifting the earnings profile $f(j)$ up or down.

$$h_{A,j+1} = h_{A,j} + a(h_{A,j}n_j)^{\alpha_1}(d_j)^{\alpha_2}, \; where \; \alpha_1 + \alpha_2 < 1 \tag{1.3}$$

$$h_{R,j+1} = \eta f(j) \tag{1.4}$$

Lifetime occupational choices, and implied earnings, depend on the realizations of initial conditions $(a, h_{A,1}, \eta)$. The realizations of $h_{A,1}$ can be such that an agent finds it optimal to work in an abstract occupation from the first period of the working life cycle, i.e., the condition in Inequality 1.2 is satisfied from $j = 1$. At the same time, with sufficiently low realizations of a and $h_{A,1}$ and/or high productivity in routine occupation

η, a portion of agents choose to work in routine occupations in the course of all J periods.

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

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

1.4 Price Series for Human Capital in Abstract and Routine Occupations

1.4.1 "Flat Spot" Approach

The application of models with endogenous human capital accumulation, including the one developed in this paper, is associated with the well-known problem of underidentification. It follows from the equation defining the y_j in Optimization problem 1.1 that, over the working life cycle, changes in individual's earnings can be attributed to either changes in the price of human capital $P_{k,t}$ or in the stock of an individual's human capital $h_{k,j}$. While the product of $P_{k,t}$ and $h_{k,j}$ can be observed in the data as the individual's hourly wage, $P_{k,t}$ and $h_{k,j}$, cannot, in general, be separated from each other. At the same time, since the partial equilibrium model described in the previous section takes the prices of human capital as exogenously given and has human capital accumulated endogenously over the working life cycle, it is important to be able to estimate the price series for human capital separately from the changes in human capital stock.

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

Equation 1.5 expresses these changes for mean log-hourly wages of agents in the model. Shocks to human capital in abstract occupations are i.i.d. and mean-zero and therefore, in the absence of selection to and out of an abstract occupation, changes in wages are driven by the changes in $P_{A,t}$ over time.

$$\begin{gathered} Mean[ln\ h_{A,j+1}] = Mean[ln\ h_{A,j}] \implies \\ Mean[ln\ P_{A,t+1} h_{A,j+1}] - Mean[ln\ P_{A,t} h_{A,j}] = ln\ P_{A,t+1} - ln\ P_{A,t} \end{gathered} \tag{1.5}$$

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

$$Mean[ln\ P_{R,t+1} h_{R,j+1}] - Mean[ln\ P_{R,t} h_{R,j}] = ln\ P_{R,t+1} - ln\ P_{R,t} \tag{1.6}$$

The model-based identification strategy expressed in Equations 1.5 and 1.6 suggests that the price series can be estimated on cross-sectional CPS data from Equation 1.7.

Here, the changes in prices are calculated as changes in mean hourly wages for synthetic cohorts of workers in abstract and routine occupations. Synthetic cohorts are formed out of workers of age j in year t and workers of age $j+1$ in year $t+1$.

$$\begin{aligned} Mean[ln\ h_{k,j+1}] =& Mean[ln\ h_{k,j}] \implies Mean[ln\ P_{k,t+1}h_{k,j+1,t+1}] - Mean[ln\ P_{k,t}h_{k,j,t}] \\ &= ln\ P_{k,t+1} - ln\ P_{k,t},\ where\ k \in \{A, R\} \end{aligned} \tag{1.7}$$

Equation 1.7 identifies price series for human capital in abstract and routine occupations only in the absence of ability-based selection to and out of these occupations. However, as is evident from Figure 1.3, mobility with the signs of ability-based selection between routine and abstract occupations persists until the later stages of the working life cycle. For instance, switches out of abstract occupation would be more frequent for agents with the lower stock of human capital and ability. For these agents, shocks to human capital are more likely to decrease their wages up to the level when they will be better-off working in routine occupations. An increase in mean earnings, associated with an increase in mean ability due to selection out of abstract occupations, would then be erroneously attributed to growth in the price of human capital in abstract occupations. On the other hand, a rise in prices for abstract human capital and a fall in prices for routine human capital would make relatively less-able agents from routine occupations enter abstract occupations. This would lead to a fall in mean ability, and human capital, of agents in abstract occupations, masking a rise in prices of human capital in this occupational category. Moreover, in the CPS data there is mobility between the two occupational categories included in the model and the categories of service occupations, unemployment, and non-participation. The ability-based selection into and out of abstract and routine occupations associated with these additional labor force statuses can further bias the estimates.

Given that selection into and out of abstract and routine occupations contributes to a change in mean hourly wages with opposite signs, it is difficult to predict the sign of the resulting bias that it introduces to the price series estimated based on Equation 1.7. However, it is possible to choose a subset of the population for which mobility into and out of the occupation would be minimized, therefore minimizing the bias arising from it.

1.4.2 Occupational Mobility Across Educational Groups

To determine the groups with the lowest mobility, I make use of the longitudinal Annual Social and Economic Supplement of CPS data (ASEC CPS), in which individuals are observed for two consecutive years. The four panels of Figure 1.3 show mobility into and out of abstract and routine occupations for college, some college, and high school workers in their respective flat spot age ranges[5]. The flat spot age ranges are 50-59 for college, 48-57 for some college, and 46-55 for high school, as suggested by Bowlus & Robinson (2012) and are chosen to minimize the cohort effects on the estimated price series. Using the individual observations in the consecutive years, the share of agents leaving the respective occupation in year t is calculated as the share of all agents reporting that occupation as the primary one in year $t-1$ and switching to another occupation, unemployment or non-participation in year t. The share of agents joining the occupation in year t is calculated as the share of all agents reporting that occupation as the primary one in year t who are observed in a different occupation, unemployment or non-participation in year $t-1$.

The top-left panel of Figure 1.3 shows that the share of agents leaving abstract occupations in each year is lowest for the college education group, oscillating around 10 per cent annually. The shares of workers with some college and high school education leaving abstract occupations are much higher, more volatile, and possess an apparent upward trend. If workers with some college and high school education are, on average, of lower ability than college workers, the upward trend in the shares of workers leaving abstract occupations can impose an upward bias on the estimates of human capital price in abstract occupations. Over time, this bias may result in a (steeper) upward trend in the estimated prices series. The higher volatility of the shares of some college and high school workers leaving abstract occupations is likely associated with the smaller shares of workers from these education groups working in abstract occupations.

A similar pattern is observed for the shares of workers joining abstract occupations (bottom-left panel of Figure 1.3). High school and some college workers in their flat spot age ranges join abstract occupations more frequently than workers with college education, and the shares of those joining increase over time. With the average ability of some college

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

and high school workers being lower than for college workers, an increase in the shares of these workers joining abstract occupations potentially biases downwards the estimated price of human capital in abstract occupations.

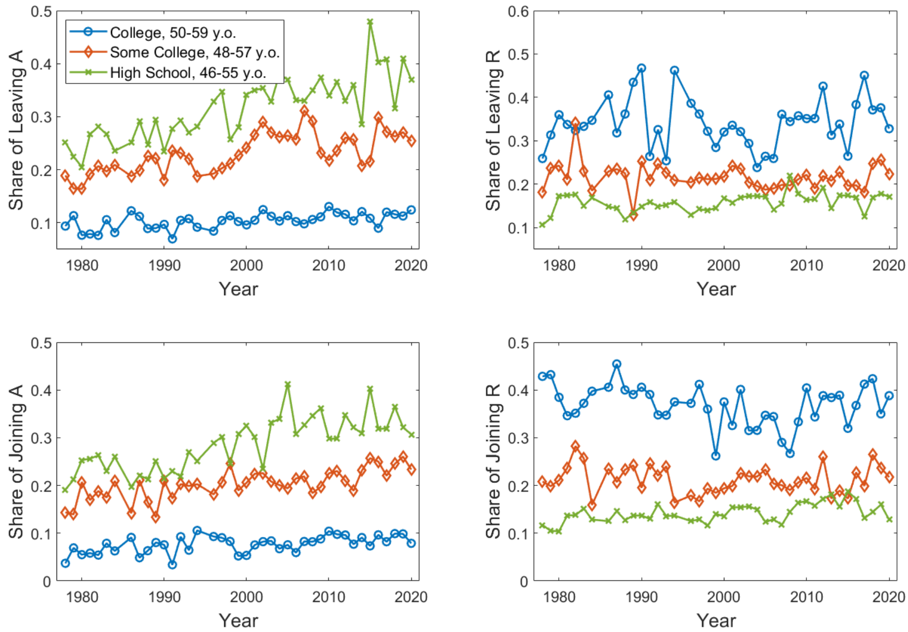

Figure 1.3: Mobility into and out of Abstract and Routine Occupations by Education Groups

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

The top- and bottom-right panels of Figure 1.3 demonstrate the shares of workers from different educational groups leaving and joining routine occupations. In contrast to abstract occupations, the lowest mobility into and out of routine occupations is observed for high school workers. The highest shares of workers leaving and joining routine occupations are observed for college workers. The shares of college and some college workers moving into and out of routine occupations are more volatile over time than those for high school workers. There are no apparent upward trends into mobility to and out of routine occupations for any educational group that would persist for the whole period under investigation. However, the shares might increase or decrease over shorter periods of time. For instance, for some college workers there is an increase in the share of those joining routine occupations between 1994 and 2006. The share of college workers joining routine occupations tends to decrease on average between 1976 and 2009.

While all of the changes in the shares of workers leaving and joining abstract and routine occupations cannot be reproduced within the simple partial equilibrium framework used in this paper, the model can be used to rationalize some of the trends and relative frequencies of the mobility in between of the two occupational categories. From the perspective of the model, workers with some college and high school education are characterized by low to medium values of human capital in abstract occupations. In the course of RBTC, as human capital prices in abstract, as well as routine, occupations are changing, larger shares of such workers find themselves better off working in abstract occupations (inequality 1.2 is satisfied for the larger share of workers), thereby producing an overall upward trend in the shares of some college and high school workers joining abstract occupations. At the same time, as workers with lower ability and human capital in routine occupations switch to abstract occupations, a larger share of them falls back to routine occupations as a result of a negative human capital shock hitting the relatively small human capital stocks of the switchers. In the model, workers with college education correspond to agents with medium to high levels of human capital in abstract occupations. Most of these workers found it optimal to supply abstract labour at the beginning of the period studied. Hence, for them the mobility into and out of the abstract occupations is the lowest of the three education groups.

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

In addition to the mobility analysis based on Figure 1.3, I formally test for the presence of differences in time trends in the log hourly wages between workers staying in their respective occupations and those who join or leave them. The analysis is conducted for the "Flat Spot" age ranges. Tables 1.A4 and 1.A5 in the Appendix show the results of the regressions of log hourly wages on the linear time trend, dummy for either joining or leaving an occupation, and interaction term between joining/leaving dummies and time trend. The coefficients on the interaction terms are insignificant for almost all education groups in both abstract and routine occupations, with the only marginally significant coefficient on the interaction term being for high school workers joining abstract occupations. This suggests that the mobility between abstract and routine occupations was not driven by workers with statistically higher or lower wages. From this it follows that the mobility observed is not likely to affect the trend in the price series for human capital in abstract or routine occupations. However, it should be noted that in these regressions, the sample sizes for some college and high school workers in abstract occupations and college and some college workers in routine occupations are at least two times smaller than the samples of college workers in abstract occupations and high school workers in routine occupations. Smaller sample sizes, and higher volatility over time of the shares of workers joining and leaving the two occupations, suggest that the estimates for some college and high school workers in abstract occupations and for college and some college workers in routine occupations can be unreliable.

1.4.3 Estimated Price Series

Figure 1.4 demonstrates the price series for human capital in abstract and routine occupations estimated on the cross-sectional CPS data. As suggested by Bowlus & Robinson (2012), to avoid the problem of wage top-coding, means from Equation 1.8 are replaced with medians. Therefore, the actual equation used to estimate the price series takes the form:

$$\begin{aligned} Med[ln\ h_{k,j+1}] =& Med[ln\ h_{k,j}] \implies Med[ln\ P_{k,t+1}h_{k,j+1,t+1}] - Med[ln\ P_{k,t}h_{k,j,t}] \\ &= ln\ P_{k,t+1} - ln\ P_{k,t},\ where\ k \in \{A, R\} \end{aligned} \tag{1.8}$$

The baseline estimates presented here are calculated for the unrestricted sample of males, (who worked at least 25 hours in the previous year) who reported positive earnings. For both occupations in Figure 1.4, prices are normalized to 1 for 1976. I also estimate the prices using a full time, full year sample (worked at least 1400 hours in the previous year) and the sample with the same restrictions on hours as for the life-cycle moments calculated on NLSY79 data (between 520 and 5820 hours worked in the previous year). The estimated price series based on these alternative samples are available in the Appendix (Figures 1.A1 and 1.A2) and are qualitatively and quantitatively similar to the baseline series.

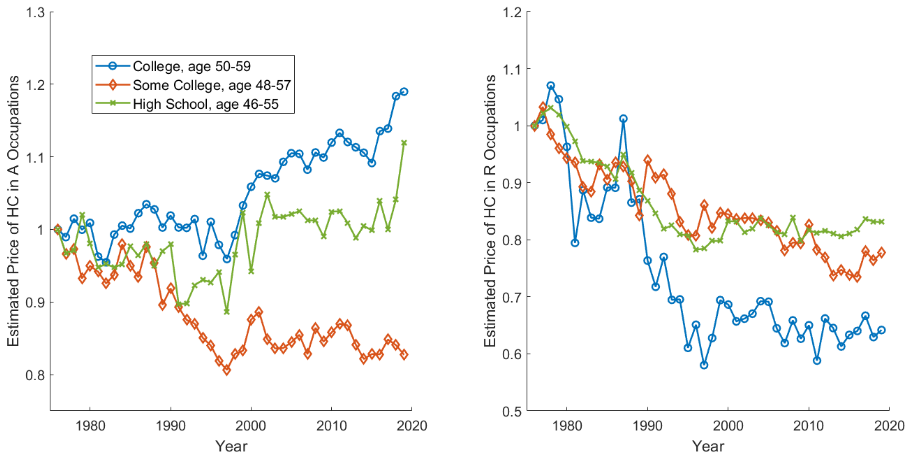

Figure 1.4: Price Series for Human Capital in Abstract and Routine Occupations
Note: Prices are calculated using cross-sectional CPS data. The sample includes all workers with positive earnings who reported working at least 5 hours a week for at least 5 weeks in the previous year and with valid observations of occupational codes.

Price series for human capital in abstract occupations estimated on the sample of college workers (left panel of Figure 1.4) suggest that the price for human capital in abstract occupations increased by more than 18 per cent from 1976 to 2019. The growth in human capital prices in abstract occupations was not monotonous: prices rose from 1982 to 1987, then fell until 1997. From 1997, interrupted by short periods of busts, the prices for human capital in abstract occupations were booming, showing a 23 percentage point increase by 2019.

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

The right panel of Figure 1.4 plots the estimates of prices for human capital in routine occupations. Unlike the estimated price series for abstract occupations, all three series of human capital prices in routine occupations demonstrate a large degree of co-movement: the steepest fall in prices for human capital in abstract occupations occurred between 1978 and 1997, with an overall flattening of the trends at the beginning of the 2000s. For high school workers, by 1997 the prices had decreased to 0.78 per cent of the 1976 price level. After a short period of recovery, between 1998 and 2000, the series shows a virtually flat time trend, with the human capital price in 2019 equal to 83 per cent of that in 1976. Prices estimated on the sample of workers with some college are moving closely with those for high school workers, but also show some steeper fall after 2010. The largest fall in the prices for human capital in routine occupations is observed for college workers – the educational group with the highest and most volatile mobility rates to and from routine occupations.

The estimated price series can be compared with the human capital price series estimated by Bowlus & Robinson (2012). The authors show that, over the same period of time, there is a high degree of comovement between human capital prices across all education categories. Figure 1.4 shows that, for college and high school workers, there is some comovement within occupational categories. At the same time, conditional on education category, prices for human capital tend to move in the opposite directions for workers employed in routine and abstract occupations. In addition, the degree of comovement between human capital prices, calculated for different education groups within occupational categories, is lower than for the price series using a division based only on the education categories.

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

Overall, college workers in abstract occupations and high school workers in routine occupations in their "flat spot" age ranges demonstrate the lowest and the least volatile rates of mobility. It is also possible to show that there is no statistically significant difference between the time trend for the workers from these educational groups who join or leave the respective occupations and those who remain in them. This suggests that for college workers in abstract occupations and high school workers in routine occupations the estimated price series of human capital can be considered to be the least biased. In the following sections, I calibrate the working life cycle model described in Section 1.3 and perform counterfactual exercises using human capital prices in abstract occupations estimated for college workers as $P_{A,t}$ and human capital prices in routine occupations estimated for high school workers as $P_{R,t}$.

1.5 Calibration and Model Fit

1.5.1 Calibration

The parameters of the model are calibrated in two stages and consolidated in Table 1.2. First, the parameters, including discount rate and the prices for human capital in abstract and routine occupations, are set without simulating the model. Discount factor β is set to 0.96, in line with Huggett et al. (2006). The number of lifetime periods (J) equals 41, with agents living from a real age of 18 to 58. Agents in the model are assumed to be aged 18 in 1976. The age premium in routine occupations takes the form $f(j) = \beta_0 + \beta_1 j + \beta_2 j^2$, where coefficients come from the equation $log(y_{j,t}) = \beta_0 + \beta_1 j + \beta_2 j^2 + \gamma_1 t + \gamma_2 t^2 + \epsilon_{j,t}$ estimated on the PSID data with the same sample restrictions as for the NLSY79 data.[6]

Human capital prices follow the second order polynomials fitted to the price series estimated in the previous section. Prices for human capital in abstract occupations are based on the flat spot age range estimates for college workers, while prices for human capital in routine occupations are based on the estimates obtained for the high school workers. The prices, as well as the fitted second order polynomials used in the model, are plotted in Figure 1.A3 in the Appendix.

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

Table 1.2: Parameters of the Model

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

Next, the model is simulated to calibrate a vector ψ of 14 values: the parameters of the initial distribution of a, h_0 and η, set to be joint log-normal; abstract human capital function elasticities α_1 and α_2; variances of shocks to human capital in abstract and routine occupations, set to be normally distributed with zero mean; the price ratio $\frac{P_{R,t}}{P_{A,t}}$ in year 1976. The parameters are chosen so that the simulated model is able to reproduce a set of moments from the NLSY79 data. Specifically, the calibration procedure targets the age profiles of the abstract wage premium and the variance of log earnings (from the age of 23 to 57). Figure 1.A4 in the Appendix shows both estimated profiles. Additionally, routine and abstract occupational distributions by ability quartiles, at the of age 25 (Figure 1.1), and RA and AR switch probabilities (Figure 1.2) are used as the targets. The calibration procedure also directly targets the share of routine workers at the age of 25. The parameters in a vector ψ are chosen to minimize the sum of squared log distances between the moments produced by simulating the model and their counterparts from the NLSY79 data.

1.5.2 Model Fit

Figure 1.5 demonstrates the fit of the model to the first set of data moments. The model-based abstract wage premium profile closely follows its data counterpart. The model is able to reproduce not only the the magnitude of the variance of log earnings over the working life cycle of the NLSY79 cohorts, but also the U-shape of the profile. The model-based variance, however, reaches the bottom of the U-shape 3 years later (at the age of 35) than the data-based profile (at the age of 32). There is a trade-off between fitting the variance and occupational mobility profiles: higher mean ability a makes it possible to reproduce the RA switches more closely, while postponing the moment when the earnings of high ability agents overtake the earnings of the low-ability agents – the point where the bottom of the U-shape occurs[7]. There is a close fit of the distribution of workers by ability quartiles in abstract and routine occupations at the age of 25. The model generates ability-based selection into two occupational categories, with the probability of an agent being observed in an abstract (routine) occupation rising (falling) in ability a.

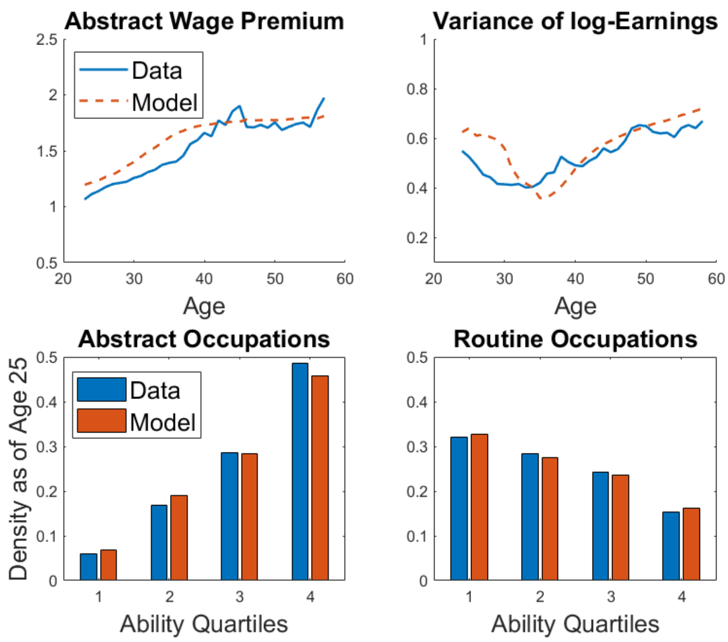

Figure 1.5: Model Fit: Earnings Statistics and Ability Distributions

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

RA and AR mobility produced by the model is compared with RA and AR mobility in

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

the NLSY79 data in Figures 1.6 and 1.7. Overall, the model is able to reproduce the RA mobility patterns observed in the data: the probability of an RA switch rises with ability. The probability of an RA switch at the beginning of the working life cycle is also higher than in its later stages. In the model, a fall in RA mobility is observed mostly between the ages of 23-33 and 34-44, while in the data RA mobility also continues to fall between the ages of 34-44 and 45-55. In the later years of the NLSY79 data, as the workers select out of employment, the sample of abstract and routine workers is composed of workers with higher labor force attachment. In a framework featuring the accumulation of human capital, higher labor force attachment closer to the end of the working life cycle can be rationalised by a higher stock of human capital. Assuming the specificity of human capital across the occupational categories, higher labor force attachment also implies higher attachment to a particular occupational category, therefore producing a further fall in the probability of an RA switch. At the same time, in a simple model with only two occupational categories and without a non-employment option, workers in routine occupations can only choose to switch to an abstract occupation when, for example, their stock of human capital in a routine occupation is hit by a negative shock.

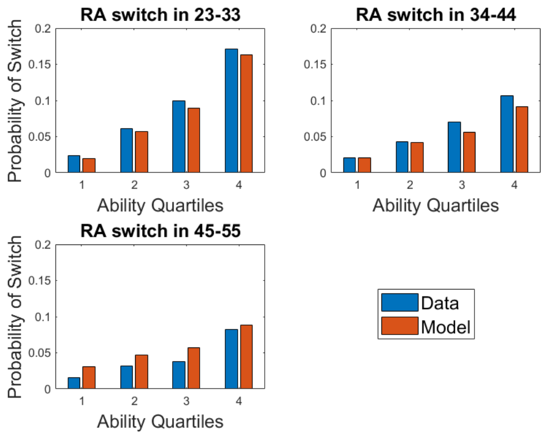

Figure 1.6: RA Mobility in the Data vs. Mobility in the Model

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

Figure 1.7 also shows the AR mobility produced by the calibrated model. The model-based probabilities of an AR switch exhibit an ability-based selection qualitatively and quantitatively similar to that observed in the data. Across all ability quartiles the probabilities of an AR switch are falling over the working life cycle. In the model developed in this study, AR switches are predominantly due to negative realizations of shocks to human capital in abstract occupations and positive realizations of shocks to human capital in routine occupations. Ability-based selection is achieved via a strong positive correlation between a and $h_{A,0}$.

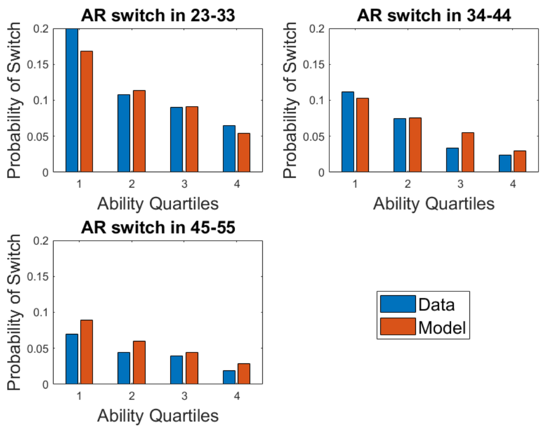

Figure 1.7: AR Mobility in the Data vs. Mobility in the Model

Note: Construction of probabilities is the same as for Figure 1.6.

1.6 Implications of the Model

1.6.1 Non-Targeted Moments

The calibration procedure described in the previous section directly targets only the share of routine workers at the beginning of the working life cycle, at the age of 23. Figure 1.8 shows how the share of routine workers in the model evolves over the whole working life cycle and compares it to the shares of routine workers in the NLSY79 data. The model closely reproduces a steep fall in the share of routine workers for the first years of the working life cycle. For the later ages, a fall in the share of routine workers implied by the model is less steep than its data counterpart. Overall, the model is able to reproduce 81 per cent of a fall in the share of routine workers between ages 23 and 54. This fall is generated by a share of routine workers who accumulate human capital to join abstract occupations later on, as well as by a simultaneous increase in the price for human capital in abstract occupations and a fall in the price for human capital in routine occupations which directly affect the Inequality in 1.2.

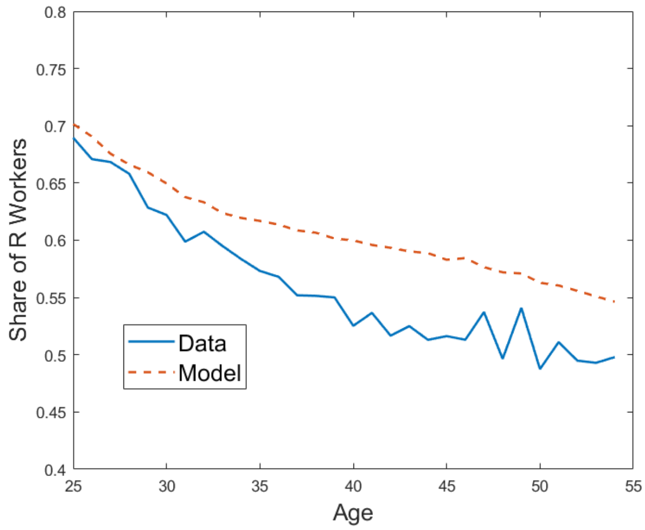

Figure 1.8: Share of Routine Workers over the Working Life Cycle

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

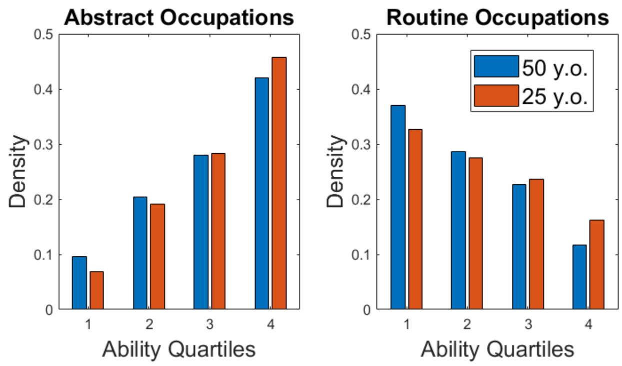

Figure 1.9: Occupational Distributions by Ability Quartiles in the Model

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

As discussed in Section 1.2.2, the initial distribution by ability quartiles in abstract occupations shows steeper ability-based selection than the final distribution (Figure 1.1). Ability-based selection into routine occupations is less strong at the beginning of the working life cycle than at the end. The calibrated model reproduces these changes in selection. As is evident from Figure 1.9, the proportion of high-ability agents in abstract occupations is higher at the age of 25 than at the age of 50. At the same time, the share of low-ability agents in routine occupations rises by the age of 50. The net outflow of workers from routine occupations produced by the model implies that some workers with medium to low ability are switching to abstract occupation over the working life cycle, therefore dampening the selection in this occupational category. In contrast, as the probability of an RA switch is rising in ability, the share of the least able agents in routine occupations increases.

Figure 1.A5 in the appendix compares the shapes of the mean earnings profiles in the NLSY79 data with those from the simulations of the calibrated model. Mean earnings increase steeply over the lifetime of the NLSY79 cohorts[8]. The calibrated model, which directly fits the abstract wage premium, closely reproduces the shape of the data-based mean earnings profile.

1.6.2 The Effect of Changes in Human Capital Prices

To see the effect of a change in human capital prices, I conduct a counterfactual exercise in which the prices for human capital in both occupational categories are kept at their 1979 levels. The rest of the parameters are set to be the same as for the calibrated full model with changing human capital prices. Figure 1.10 contrasts the resulting counterfactual simulated moments with the baseline simulations of the model where prices for human capital change as in the data. For the first 10 years of the working life cycle, the counterfactual abstract wage premium (left panel of Figure 1.10) closely follows the abstract wage premium profile produced by the full model. The reason for this is that at the beginning of the working life cycle, even with no change in the prices of human capital, workers dedicate most of their time to the accumulation of human capital and, when there is a change in the prices, they cannot increase their time investment into human capital accumulation due to the time constraint. Moreover, in the 1980s, when the NLSY79 cohorts were at the beginning of their working life cycle, the prices for human capital in abstract occupations did not show much growth, and the fall in the prices for human capital in routine occupations was gradual and were not reflected in the premium right away.

After the age of 30-33, the divergence between the profiles of the abstract wage premium becomes more apparent. For the model with changing human capital prices, a period of steep growth in the abstract wage premium, associated with the active accumulation of human capital in abstract occupations, continues almost up to the age of 40, while the abstract wage premium profile in the model with fixed human capital prices

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

starts to flatten around the age of 35. After the age of 40, the abstract wage premium in the full model continues to rise slowly, mostly due to the growth in the price of human capital in abstract occupations. The abstract wage premium under the counterfactual scenario of no change in prices shows a mild downward trend – due to the agents with on average lower human capital switching from routine to abstract occupations. By the age of 57, the change in human capital prices contributes to an increase in the abstract wage premium of 28.6 per cent.

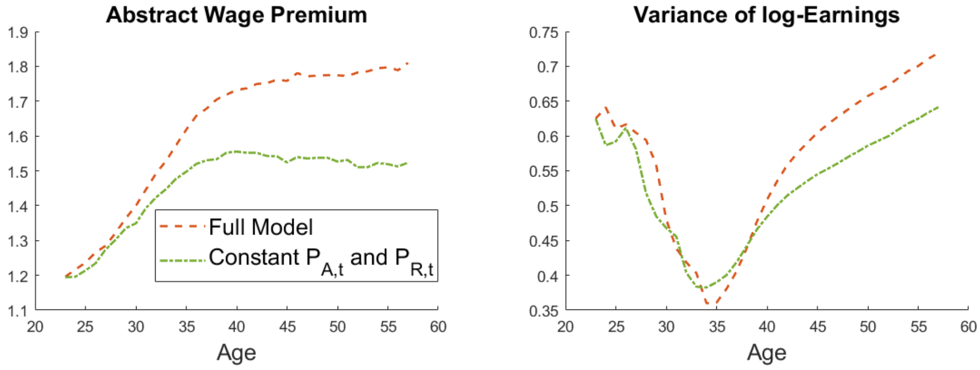

Figure 1.10: Earnings Statistics: Full Model vs. Constant Human Capital Prices

Table 1.3: Variance of log-Earnings
in the Models with Different Sources of Earnings Variation

	Age			
Model	25	35	45	55
Full Model	0.64	0.36	0.59	0.69
No growth in Prices	0.59	0.38	0.54	0.62
	(0.92)	(1.06)	(0.91)	(0.89)
No shocks	0.54	0.19	0.46	0.54
	(0.85)	(0.53)	(0.79)	(0.78)
No variation in initial conditions	0.09	0.09	0.13	0.18
	(0.14)	(0.24)	(0.2)	(0.26)

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

The right-side panel of Figure 1.10 compares the evolution of variance of log-earning in the full model and in the counterfactual with the fixed human capital prices. Most of the rise in variance due to the changing prices takes place in the second half of the working life cycle. By the end of the working life cycle, the growing gap between prices for human capital in abstract and routine occupations accounts for up to 10.8 per cent of the variance. Additionally, more active accumulation of human capital under changing prices leads to the U-shape of the profile reaching its minimum at the lower level of variance and appearing by two years later as compared to the case with the fixed prices.

Compared to other sources of earnings variation in the model, changing prices appear to have a rather modest effect on the variance of log-earnings. Table 1.3 shows the variances of log-earnings at different ages produced by the models, from which one out of three sources of variation in earnings is removed. The most important source of variation in earnings is the variation in initial conditions: the model with all agents having the same mean realization of the three initial conditions $a, h_{A,0},$ and η is able to reproduce only up to 26 per cent of the variance of the full model where initial conditions have a calibrated dispersion. The other important source of variation in earnings are the shocks to human capital in abstract and routine occupations. Around the age of 35, the model without these shocks is only able to produce just above half of the variance observed in the full model. At the same time, the model with constant human capital prices is able to produce around 90 per cent of the variance produced by the full model, with the variance around the age of 35 reaching its minimum at a slightly higher level due to the less intense accumulation of human capital under no growth in prices.

1.6.3 Human Capital Responses

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

To isolate the contribution of human capital responses, I run a counterfactual exercise in which the agents in the model with human capital prices evolving as estimated from the data do not respond to the price changes and keep following the policies optimal under the constant human capital prices. Figure 1.11 shows the results of such a counterfactual exercise for the abstract wage premium. Driven solely by price changes, the abstract wage premium under no human capital responses is significantly higher than the wage premiums calculated for the full model and for the model with fixed human capital prices. The fact that the abstract wage premium is higher under no human capital responses than in the full model, where agents are allowed to adjust their decisions to the changing prices, suggests that human capital responses serve to dampen a rise in the premium.

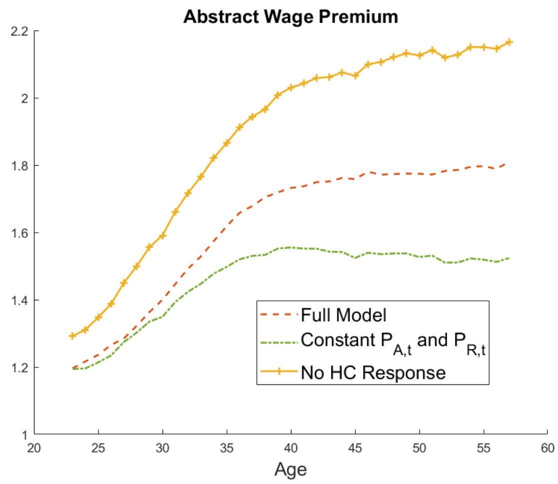

Figure 1.11: Human Capital Response and Abstract Wage Premium

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

Figure 1.12 shows a higher proportion of workers staying in routine occupations under no changes in prices. Most of the decline in the share of routine workers over the working life cycle is associated with the price changes and the resulting human capital responses. Figure 1.13 further compares the probabilities of RA switches under changing and constant human capital prices across ability quartiles. The figure suggests that the estimated changes in human capital prices lead to an increase in the RA mobility across all ability quartiles. Figure 1.A6 in the Appendix, which breaks down the human capital responses by ability quartiles, suggests that an increase in the RA mobility is actually associated with a more intensive accumulation of human capital in abstract occupations across all ability quartiles.

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

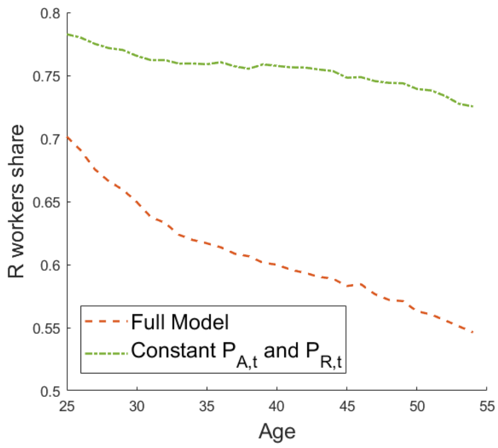

Figure 1.12: Share of Routine Workers: Changing vs. Constant Human Capital Prices

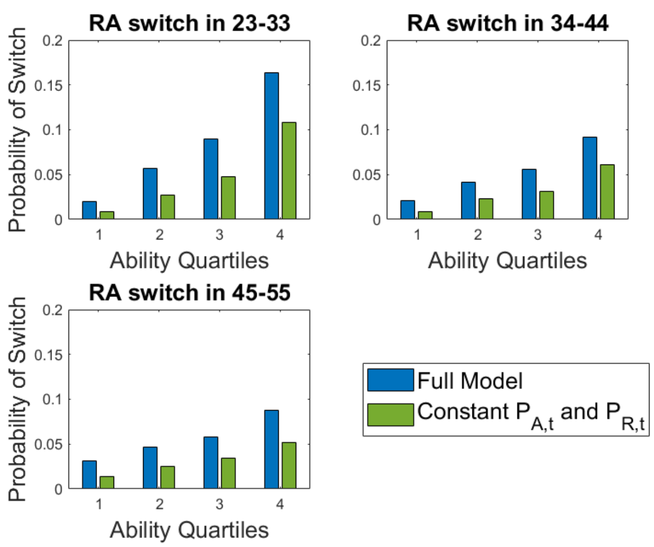

Figure 1.13: Probability of RA Switch: Changing vs. Constant Human Capital Prices

1.7 Conclusion

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

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

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

1.A Appendix

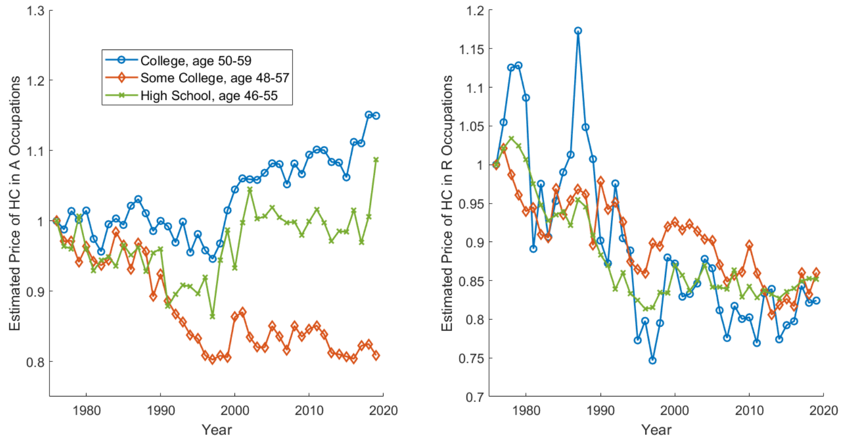

Figure 1.A1: Price Series for Human Capital in Abstract and Routine Occupations: Full-Time, Full Year Sample

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

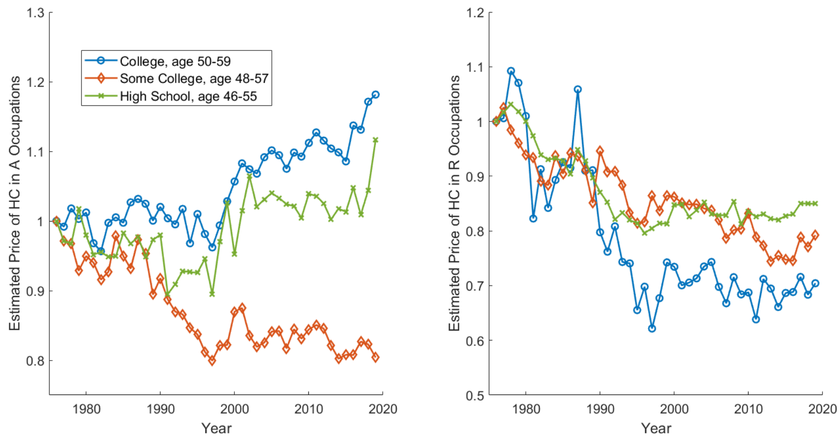

Figure 1.A2: Price Series for Human Capital in Abstract and Routine Occupations: NSLY79 Hours Sample

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

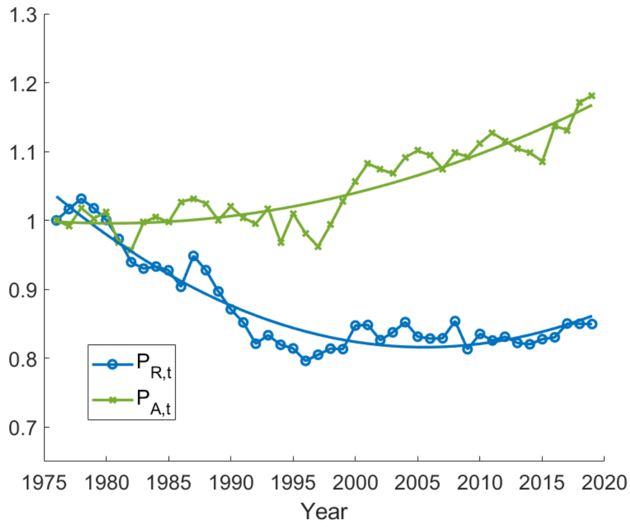

Figure 1.A3: Price Series for Human Capital Used in the Model

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

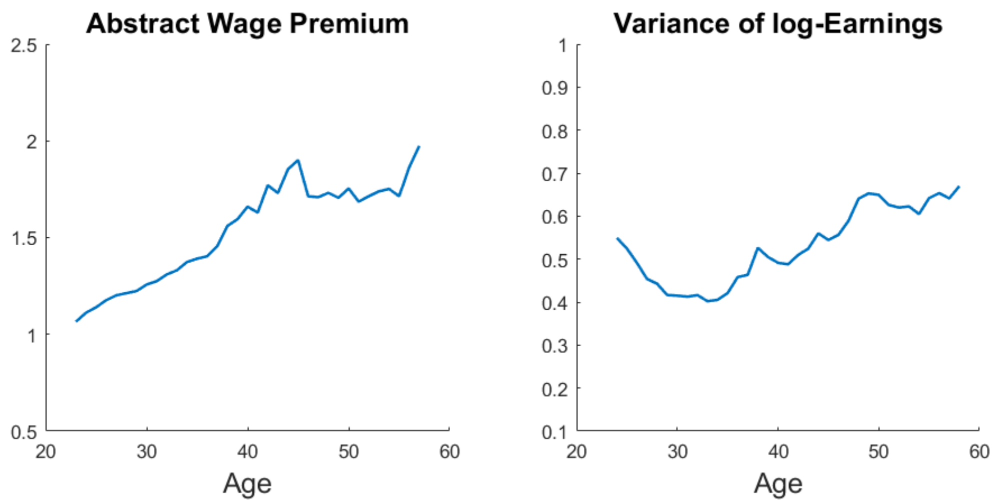

Figure 1.A4: Earnings Statistics for the NLSY79 Data

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

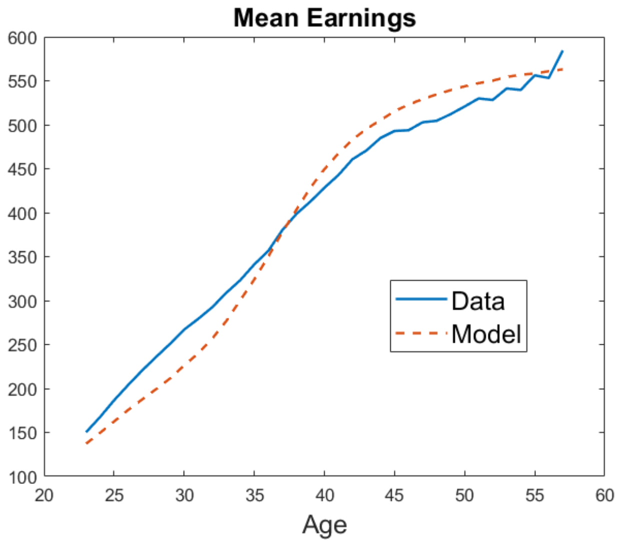

Figure 1.A5: Mean Earnings Profile: Data vs. Model

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

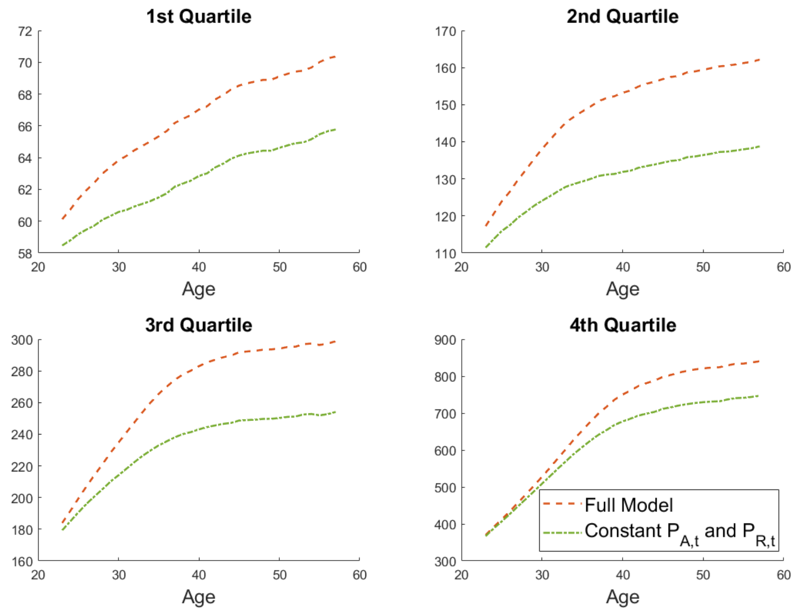

Figure 1.A6: Human Capital Responses by Ability Quartiles

Table 1.A1: NLSY79 Sample of Males by Age and Occupational Categories

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

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

Table 1.A2: Occupational Paths for Abstract Workers (by ability quartiles)

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

Note: R-routine occupation, A-abstract occupation, S-service occupation. The first three columns show the periods in which observations of occupational category are taken for each individual: in a current year, in two years and in 10 years. The last four columns show the fractions of workers from different ability quartiles following a particular occupational path. Probabilities of the occupational paths are calculated in the same manner as the switch probabilities for Figure 1.2. Here, the observations in service occupations are also included.

Table 1.A3: Labor Income across Different Occupational Paths

	Q1	Q2	Q3	Q4
***Panel 1:* Routine Occupations**				
Occ. upgrading (RRA and RAA) vs. staying (RRR)				
Occ. upgrading	0.226***	0.055	0.214***	0.247***
	(0.056)	(0.042)	(0.032)	(0.038)
Age	0.084***	0.035***	0.028**	-0.003
	(0.027)	(0.012)	(0.012)	(0.011)
Age^2	-0.001***	-0.001***	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Year	-0.001	0.026***	0.030***	0.014**
	(0.007)	(0.005)	(0.004)	(0.006)
Nonwhite	-0.033**	-0.011	0.020	-0.007
	(0.015)	(0.015)	(0.026)	(0.033)
Obs.	1736	2173	2165	1427
***Panel 2:* Abstract Occupations**				
Occ. downgrading (AAR and ARR) vs. staying (AAA)				
Occ. downgrading	-0.327***	-0.267***	-0.285***	-0.475***
	(0.116)	(0.064)	(0.045)	(0.050)
Age	-0.055	0.086***	0.026	0.043***
	(0.097)	(0.026)	(0.017)	(0.014)
Age^2	0.001	-0.001***	-0.000	-0.001***
	(0.001)	(0.000)	(0.000)	(0.000)
Year	-0.004	0.020**	0.012*	0.024***
	(0.023)	(0.008)	(0.007)	(0.004)
Nonwhite	-0.047	-0.021	0.061***	-0.039
	(0.043)	(0.033)	(0.019)	(0.026)
Obs.	223	612	1577	2947

Note: Columns Q1-Q4 show the estimated coefficients from a regression of log yearly labor income in t+10 on dummies for occupational upgrading and downgrading and a set of listed controls. The Occ. upgrading dummy is defined as equal to 1 if an individual follows an RRA or RAA (upgrading) occupational path in t, t+2, and t+10, respectively and as equal to 0 if an individual follows an RRR (staying) path; Occ. downgrading dummy is defined as equal to 1 if an individual follows an AAR or ARR (downgrading) occupational path in t, t+2, and t+10, respectively and as equal to 0 if individual follows an AAA (staying) path. Robust s.e. in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 1.A4: Time Trends in Log Hourly Wages in Abstract Occupations

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

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

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

Table 1.A5: Time Trends in Log Hourly Wages in Routine Occupations

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

Note: Regressions are estimated on the longitudinal ASEC CPS data for the educational groups in their respective flat spot age ranges. 'Joining R' is a dummy variable equal to 1 if an individual was observed in either an abstract or service occupation or non-employment in year $t-1$ and was observed in a routine occupation in year t, and equal to 0 if observed in a routine occupation in both years. 'Leaving R' is a dummy variable equal to 1 if an individual was observed in a routine occupation in year t and was observed in either a service or abstract occupation or non-employment in year $t-1$, and equal to 0 if observed in a routine occupation in both years. Samples for joining and leaving are constructed the same way as for Table 1.A4.
Robust s.e. in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Chapter 2

Disappearing Stepping Stones: Technological Change and Career Paths[1]

2.1 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 et al., 2003b, 2006a; Acemoglu & Autor, 2011b; Autor & Dorn, 2013b). 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 & Autor, 2011b). This reallocation has been studied along several dimensions. Cortes et al. (2017b), 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 (2016b) 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

[1]**Co-authored with Valentin Artemev (CERGE-EI)**

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 & Dorn, 2009b).

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 2.2, we describe the relevant literature. In Section 2.3, we perform an empirical assessment of the bottleneck effect as an implication of the change in employment opportunities due to RBTC. Section 2.4 builds the structural model, which is further parameterized and estimated in Section 2.5. Finally, Section 2.6 discusses the fit of the model and its estimated parameters, and runs a set of counterfactual exercises to quantify the bottleneck effect. Section 2.7 concludes.

2.2 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 et al. (2003b), Autor et al. (2006a), Goos & Manning (2007b), and Acemoglu & Autor (2011b) 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, 2010b). 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 (2016b), 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 & Dorn (2009b) specify demographic groups that are likely to be more affected by RBTC, while Cortes et al. (2017b) 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 et al. (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 (2016b) and Jung & 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 & Wolpin (1997) and Yamaguchi (2012a), and with the model of occupational mobility based on occupation-specific experience from Kambourov & Manovskii (2009b). 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.

2.3 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, 2010b; Cortes et al., 2017b). 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.

Table 2.1: 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

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[2]: non-routine cognitive (NRC), routine cognitive (RC), routine manual (RM), and non-routine manual (NRM), as described in Table 2.1.

Figure 2.1 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 well as a downward net-mobility towards low-skilled jobs among workers who become closer to retirement.

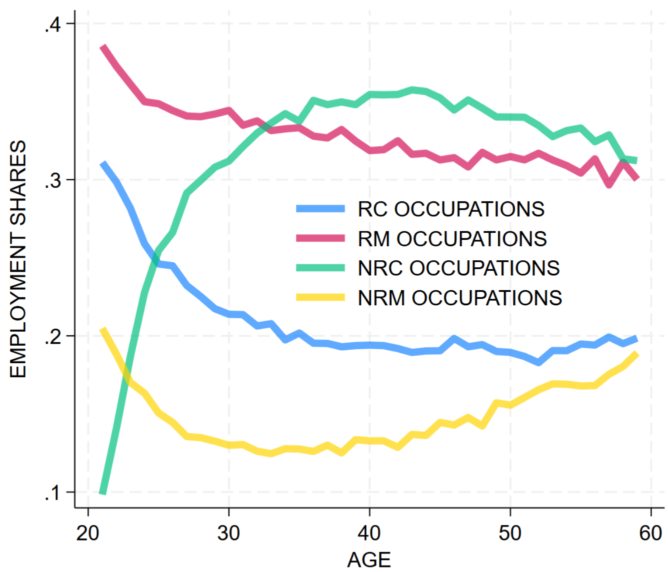

Figure 2.1: Employment shares in the three broad occupational categories over age

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

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.[3] As such, we reduce individual employment histories to broad occupational career paths.

Table 2.2: 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.

Table 2.2 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,

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

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 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 3.A, describing all observed career paths that end in NRC occupations (Table 2.A1), as well as in other labor states (Tables 2.A2 —2.A5).

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 (2016b). 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.[4]. Next, we set up the binary specification outlined below:

$$
\begin{aligned}
I^*_{itc} = & \eta_0 + \boldsymbol{\omega} \cdot \boldsymbol{cohort_c} + \boldsymbol{\theta} \cdot \boldsymbol{ind\_ctrl_i} + \boldsymbol{\psi} \cdot \boldsymbol{agg\_ctrl_t} + \epsilon_{itc}, \qquad (2.1)\\
& \text{so that} \\
& \quad I^*_{itc} > 0, \quad \text{if } I_{itc}\left(occ_{>30} = E\right) = 1, \\
& \quad I^*_{itc} \leq 0, \quad \text{if } I_{itc}\left(occ_{>30} = E\right) = 0.
\end{aligned}
$$

and estimate it separately for each state E. In equation (2.1), $cohort_c$ 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,

[4]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

$cohort_c^{1975} = 1$, while $cohort_c^{1975} = 0$ 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.

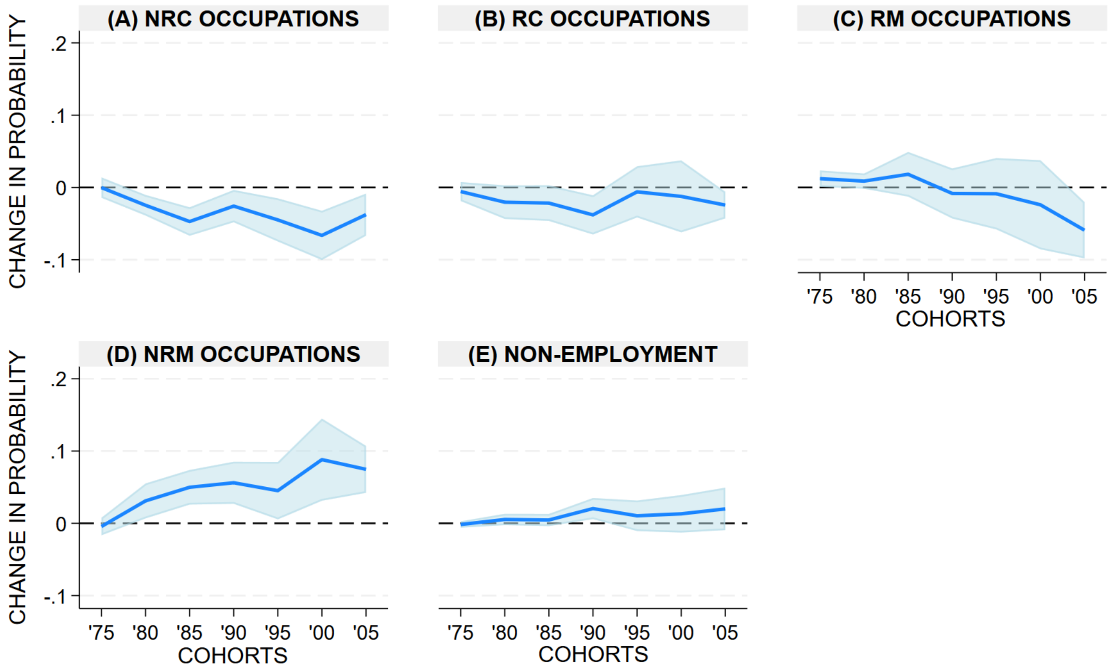

Figure 2.2: Changes by cohorts in the probability of being employed in a particular group of occupations in the prime to old age

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.

We estimate the specification in equation (2.1) using logit estimator. Figure 2.2 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 2.2 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 2.2 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. In contrast, the probability of employment in NRM occupations shows a significant increase across cohorts.

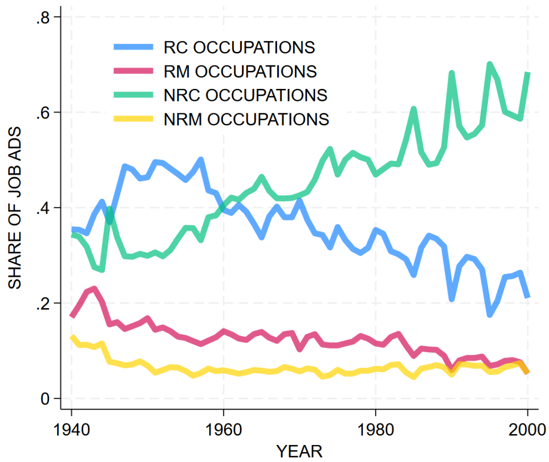

Figure 2.3: Shares of job ads by broad occupational groups, based on Atalay et al. (2020) data

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 2.1 (NRC, RC, RM, and NRM). Figure 2.3 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[5].

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 (2.2).

$$\begin{aligned} I_{it}(occ_{old} = NRC) = & \eta_0 + \eta_1 \cdot RC\_adshare_t + \eta_2 \cdot RM\_adshare_t + \eta_3 \cdot NRC\_adshare_t + \\ & + \gamma \cdot I_i(t \geq 1980) + \boldsymbol{\theta \cdot ind\_contrl_i} + \boldsymbol{\psi \cdot agg\_contrl_t} + \epsilon_{it} \end{aligned} \tag{2.2}$$

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 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 2.3 shows the estimation results for equation (2.2). 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.

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

Table 2.3: 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.

Figures 2.4-2.5 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 2.4 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 2.5 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.[6] 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 2.A1-2.A3 in the Appendix). As we would expect, for younger workers, the probability of being employed in NRC occupations at an older age is positively 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.

[6] 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 2.3 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 2.3), allowing workers from RM occupations to join NRC more freely compared to those from NRM.

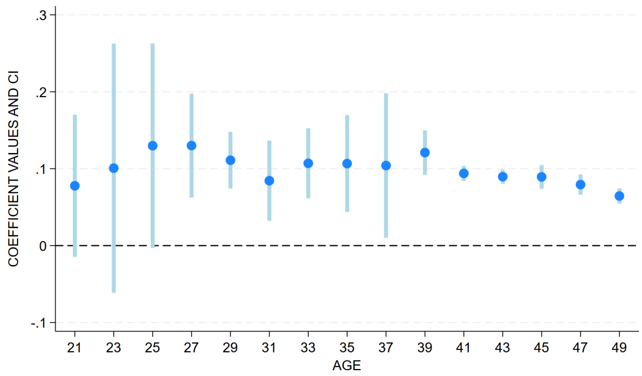

Figure 2.4: Correlation between the probability of entering NRC occupation when old and being in RC occupation when young(er)

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.

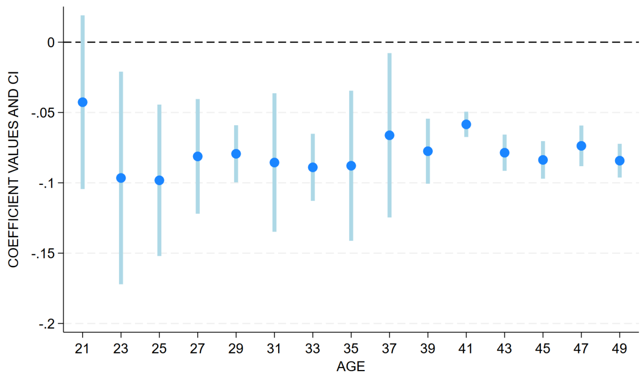

Figure 2.5: Correlation between the probability of entering NRC occupation when old and being in RM occupation when young(er)

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 2.4.

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.

2.4 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 $w_U(h_a)$[7]. Workers choose between the available employment and non-employment alternatives in each period in order to maximize their lifetime utility, i.e.:

$$\max_{\{j_a\}} E \sum_{a=s}^{3} \beta^{a-1} w_{j_a}(h_a) \tag{2.3}$$

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 & Mercenier (2014); Cortes (2016b) 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:

$$w_j(h_a) = \lambda_j \phi_j(h_a) \ , \tag{2.4}$$

[7]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 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:

$$0 \leq \frac{\partial \ln \phi_j}{\partial h_a} < \frac{\partial \ln \phi_{NRC}}{\partial h_a} \;\; \forall h_a, \text{ where } j \neq NRC. \tag{2.5}$$

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.[8] 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 (2.6) and (2.7) determining the occupational choices of workers with different levels of human capital. However, 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.

$$0 \leq \frac{\partial \ln \phi_{NRM}}{\partial h_a} < \frac{\partial \ln \phi_{RM}}{\partial h_a} < \frac{\partial \ln \phi_{RC}}{\partial h_a} < \frac{\partial \ln \phi_{NRC}}{\partial h_a} \;\; \forall h_a. \tag{2.6}$$

$$\lambda_{NRM} > \lambda_{RM} > \lambda_{RC} > \lambda_{NRC} > 0. \tag{2.7}$$

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.

[8] 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.

Specifically, human capital in the next period of lifetime is determined by:

$$h_{a+1} = b_j \cdot h_a, \text{ where } b_j \geq 0 \text{ and } j \in \{NRC, RC, RM, NRM, NE\} \tag{2.8}$$

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 2.4 summarizes the possible cases (k) and their unconditional probabilities (q_k) given known p_{NRM}, p_{RM}, p_{RC}, and p_{NRC}.

Table 2.4: 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 (2.3) 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:

$$\begin{cases} V_{a,k}(h) = \max\limits_{j \in \{\text{choice set}\}} \left\{ w_j(h) + \beta E_k V_{a+1,k}(h' \mid j) \right\}, & \text{if } a = 1, 2; \\ V_{a,k}(h) = \max\limits_{j \in \{\text{choice set}\}} \left\{ w_j(h) \right\}, & \text{if } a = 3. \end{cases} \tag{2.9}$$

where E_k denotes the expectation of the future value over 16 possible cases described in Table 2.4, 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 2.5 and 2.6 we summarize the problems solved by individuals over the lifetime in each realized case. The older workers (Table 2.5) 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.

Table 2.5: 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	$V_{3,1}(h) = \max\limits_{j \in \{C,NRC,RC,RM,NRM,NE\}} \{w_j(h)\}$
$k = 2$	NRC, RC and NRM	$V_{3,2}(h) = \max\limits_{j \in \{C,NRC,RC,NRM,NE\}} \{w_j(h)\}$
...	...	...
$k = 6$	NRC	$V_{3,6}(h) = \max\limits_{j \in \{C,NRC,NE\}} \{w_j(h)\}$
...	...	...
$k = 16$	-	$V_{3,16}(h) = \max\limits_{j \in \{C,NE\}} \{w_j(h)\}$

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 2.4, i.e.:

$$E_k V_{a,k}(h) = \sum_{k=1}^{16} V_{a,k}(h) q_k \tag{2.10}$$

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 2.6: Value functions across realization of offer arrivals, young and prime 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.

2.5 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.[9]

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 $p_{U,t}$.[10] 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 $p_{U,post}$.

[9] 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.

[10] 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.

Further, we set the productivity of human capital to be an exponential function of the current human capital stock (Equation 2.11), 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 $\sigma^2_{h_0}$.

$$\phi_j = exp(a_j h_a) \tag{2.11}$$

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 2.1) 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 categories (Figure 2.3), adjusted by the changes in the sample size of the Atalay et al. (2020) data. Formally, for any two adjacent years we set:

$$\frac{p_{j,t} - p_{j,t-1}}{p_{j,t-1}} = \Delta_{j,t} - \Delta_t \quad , \tag{2.12}$$

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 2.6 shows the estimated changes relative to the base of 1944.

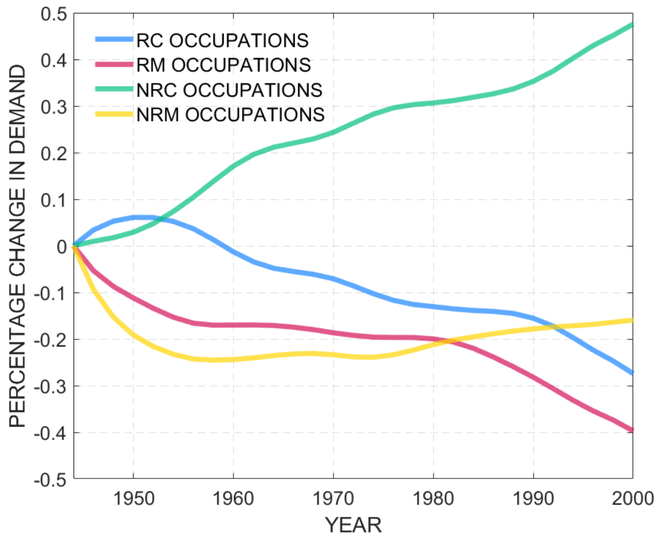

Figure 2.6: Changes in demand for jobs in 4 occupational categories based on the Atalay et al. (2020) data

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

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 & Gaggl (2018b) 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 & Dorn, 2013b), 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 2.6 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.

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 2.3 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[11] 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 occu-

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

pational 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).

2.6 Results

Model fit. Figures 2.7-2.9 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 2.7, 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 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.[12] 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

[12]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.

effects of the hollowing out of employment opportunities in RC occupations.

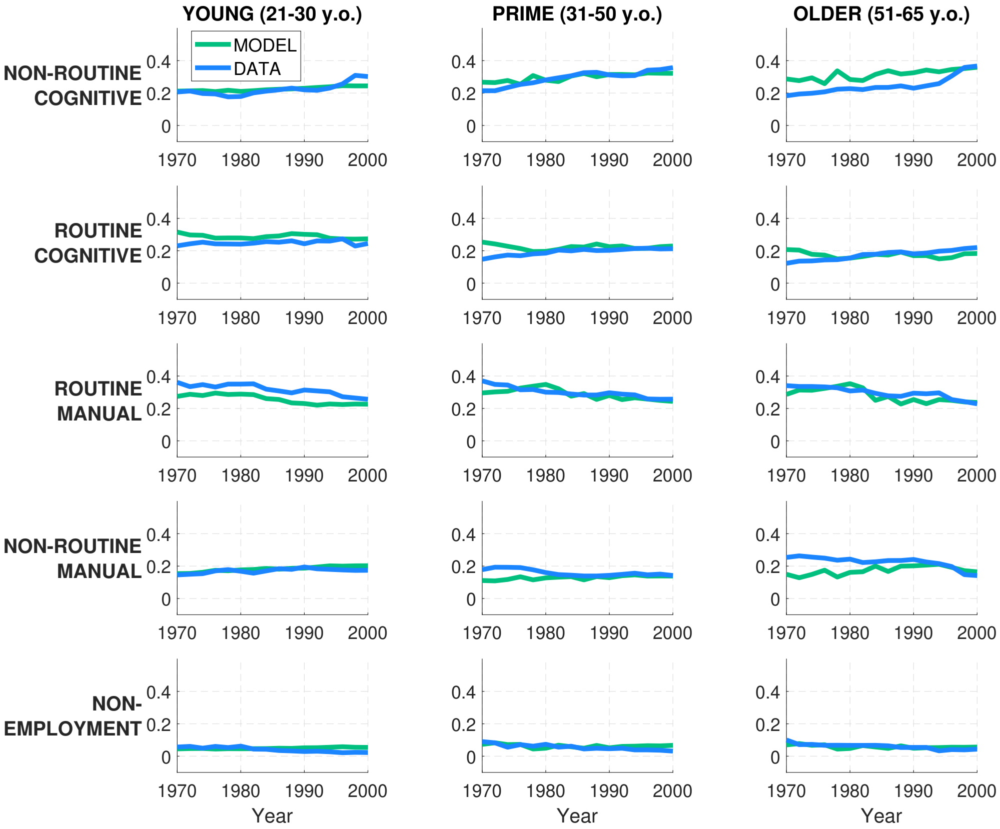

Figure 2.7: Model fit. Allocations.

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.

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 2.8), 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}.

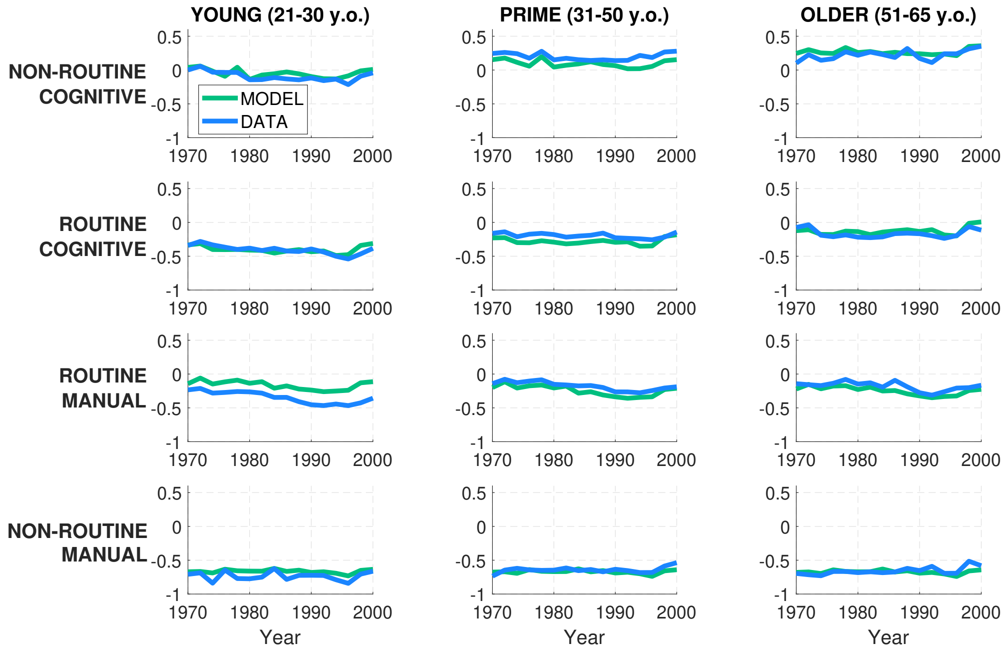

Figure 2.8: Model fit. Wages.

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 2.9, 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.

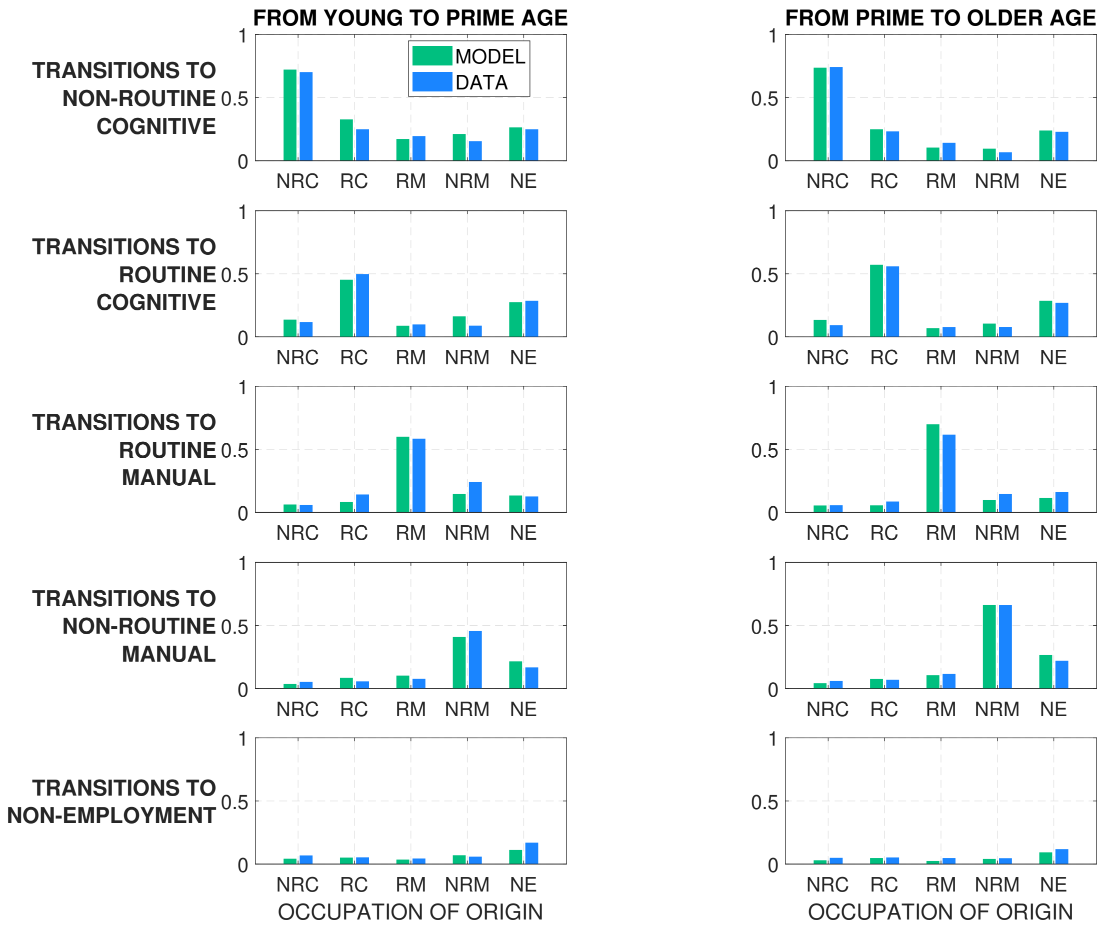

Figure 2.9: Model fit. Transition probabilities.

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 2.7 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.[13]

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.[14]

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 2.A4 (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 stock may end up in RC occupations as the probability of job offer arrival from NRC occupations is one of the lowest (Figure 2.A5). For the workers who manage to join NRC occupations, lower returns to human capital are compensated by its much faster accumulation.

[13] 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.

[14] In fact, this result is in agreement with the intuition provided by the studies considering mutlidimensional human capital (Sanders & Taber, 2012; Yamaguchi, 2012a; Lise & Postel-Vinay, 2020). For instance, Lise & 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.

Table 2.7: 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 2.A4 (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 2.A4 (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 2.A4 (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 2.A4 (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 2.A5
Separation Rate	$\{p_{U,t}\}_{t=1970...2000}$	$[0.29, 0.56]$	Figure 2.A6
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 2.A5), 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 2.10 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 2.10 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,[15] 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.

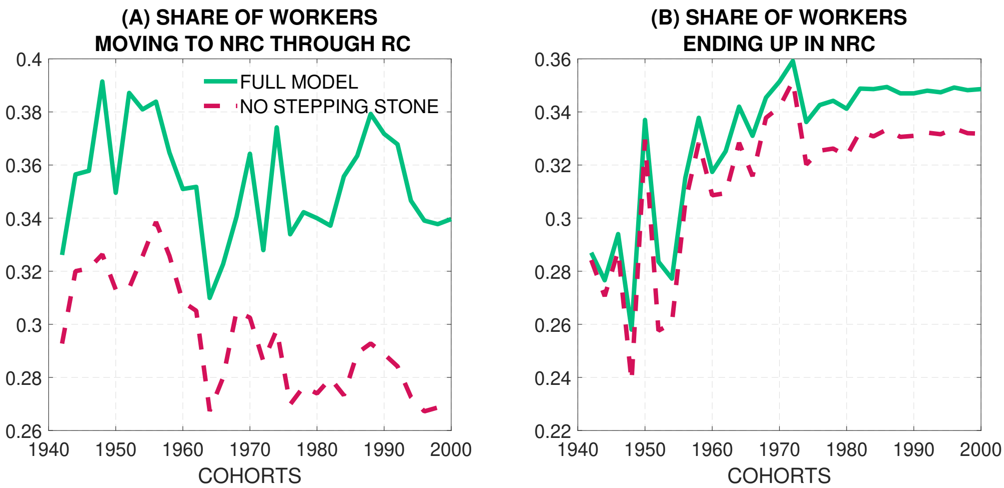

Figure 2.10: Workers' transitions to NRC occupations by older age in full and no stepping stone models

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.

[15] 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 2.A7 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 2.10, 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 2.A7, 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 2.11, 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.

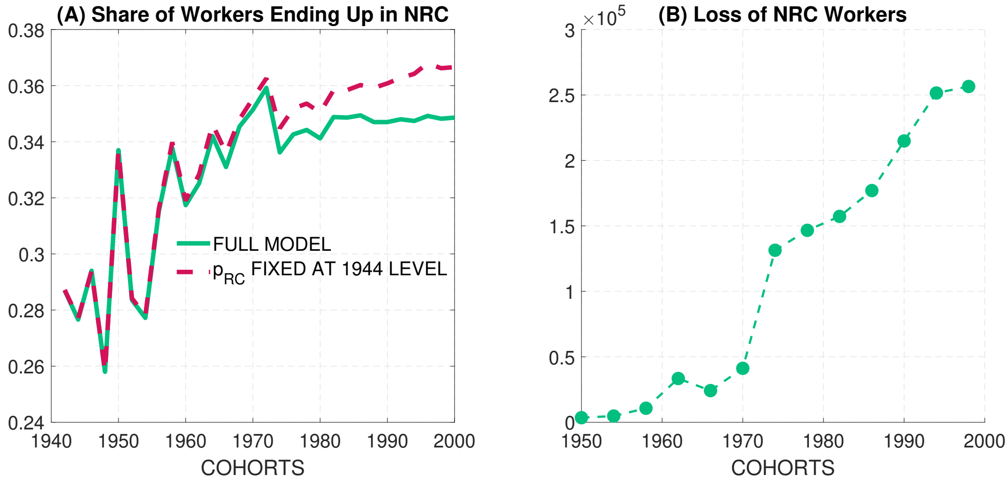

Figure 2.11: Workers' transitions to NRC occupations by older age in full and fixed $p_{RC,t}$ models

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 2.2), 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 2.11 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.[16] The number

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

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.[17] 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 2.A8 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%.[18]

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 2.12 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 2.12 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

[17] 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.

[18] As suggested by Figure 2.A8, 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.

can accumulate human capital in the absence of offers from RC 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)).

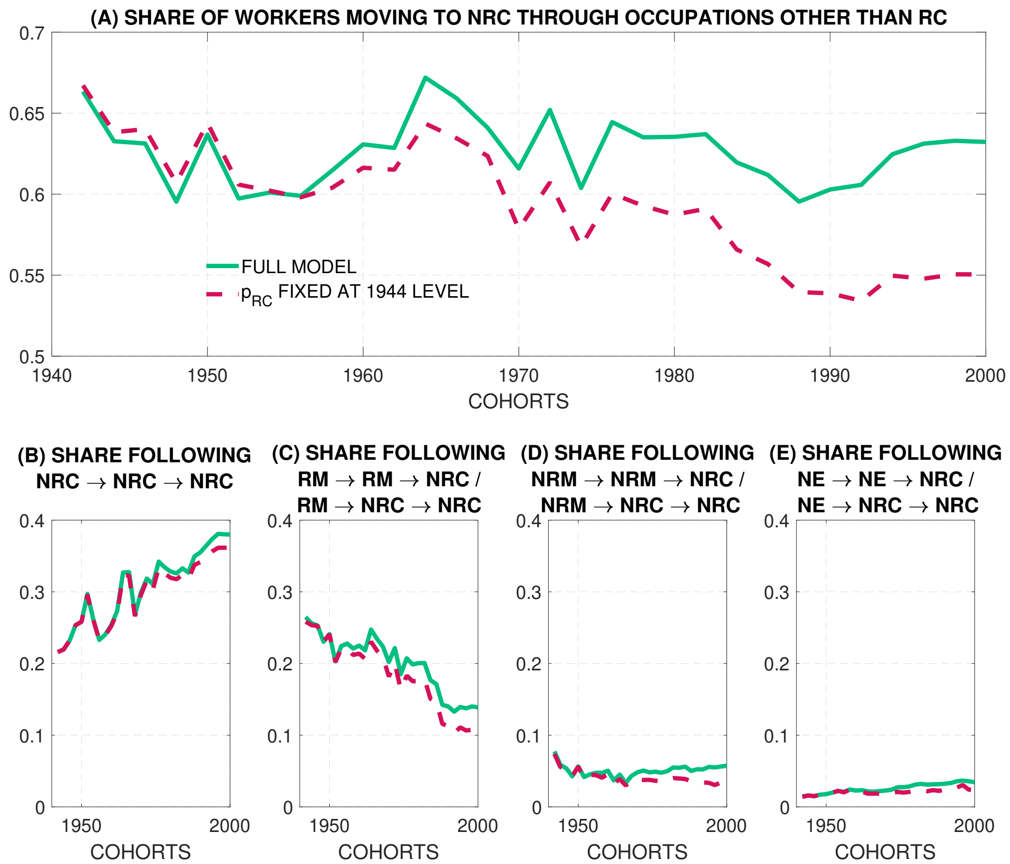

Figure 2.12: Alternative ways to reach NRC occupations

Table 2.8: 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 2.8 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 $\lambda_{NRC,t}$.

2.7 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.

2.A Appendix

Table 2.A1: 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 2.A2: 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 2.A3: Occupational paths towards routine manual occupations (RM)

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

Source: Authors' calculations on the PSID data

Table 2.A4: 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 2.A5: 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 2.A6: 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 2.A7: 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 2.A8: Occupational paths towards routine manual occupations (RM), two age groups

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

Source: Authors' calculations on the PSID data

Table 2.A9: Occupational paths towards non-routine manual occupations (NRM), two age groups

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

Source: Authors' calculations on the PSID data

Table 2.A10: 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

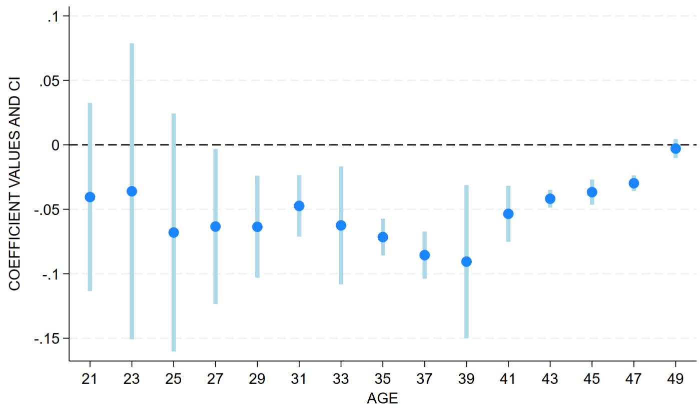

Figure 2.A1: Correlation between the probability of entering NRC occupations when old and being in NRM occupation when young(er)

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 2.4.

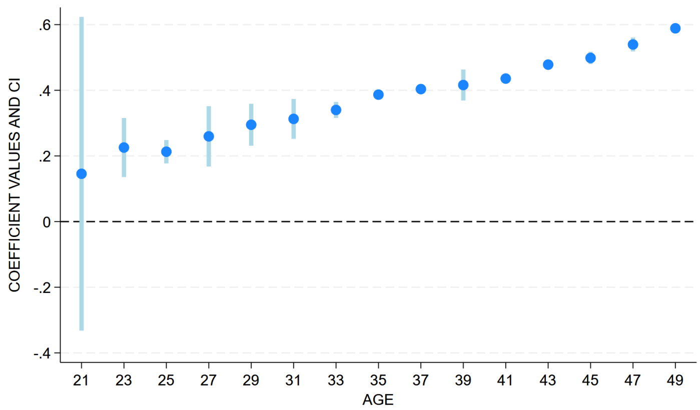

Figure 2.A2: Correlation between the probability of entering NRC occupations when old and being in NRC occupation when young(er)

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 2.4.

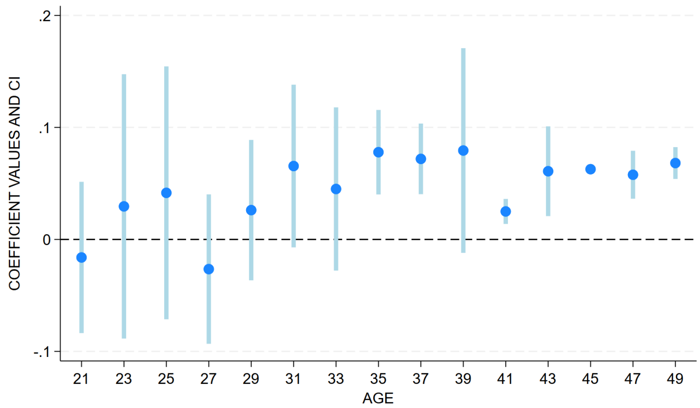

Figure 2.A3: Correlation between the probability of entering NRC occupations when old and being in NE when young(er)

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 2.4.

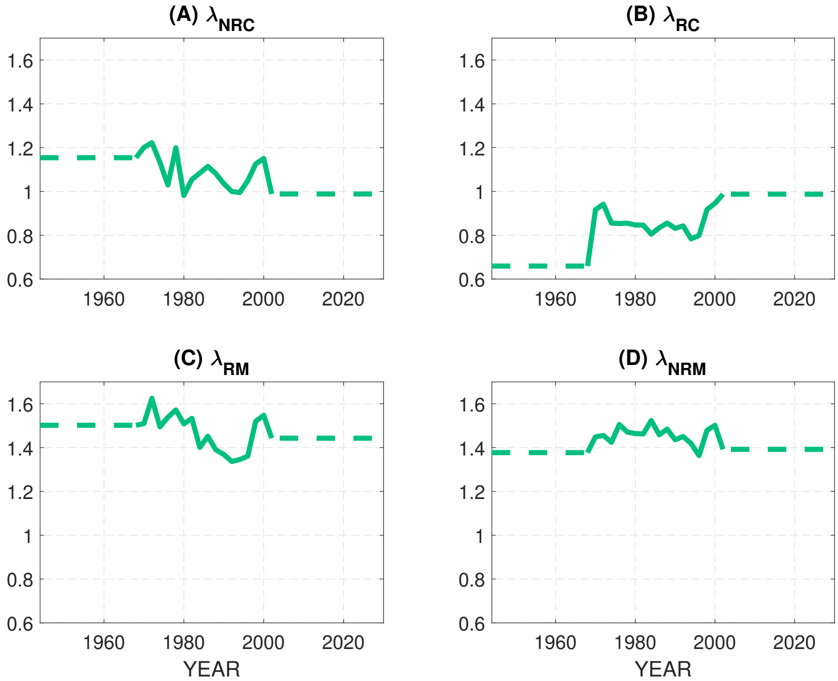

Figure 2.A4: Calibrated wage rates

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.

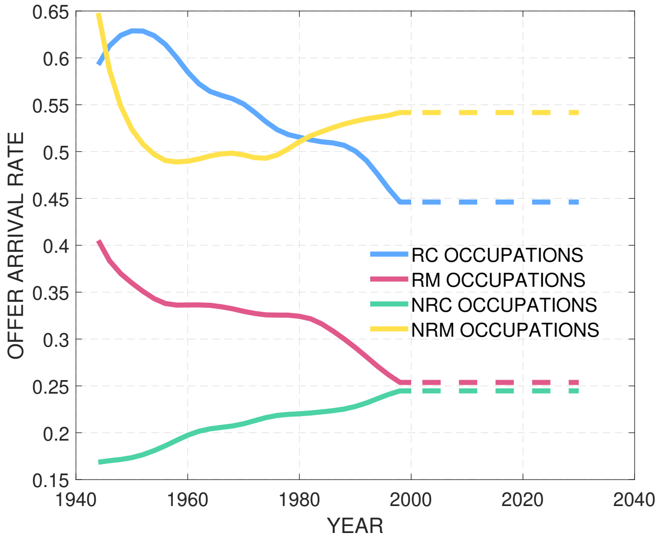

Figure 2.A5: Job offer arrival rates

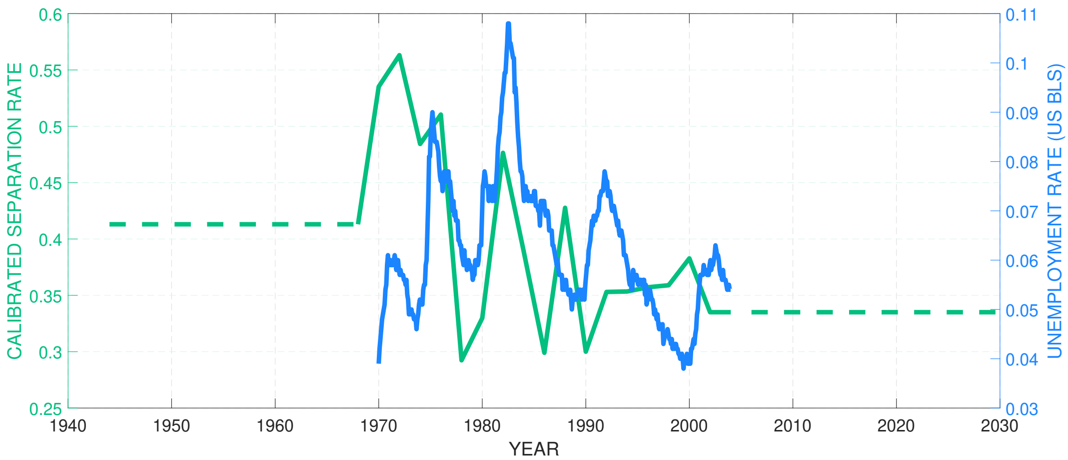

Figure 2.A6: Separation rate $p_{U,t}$

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.

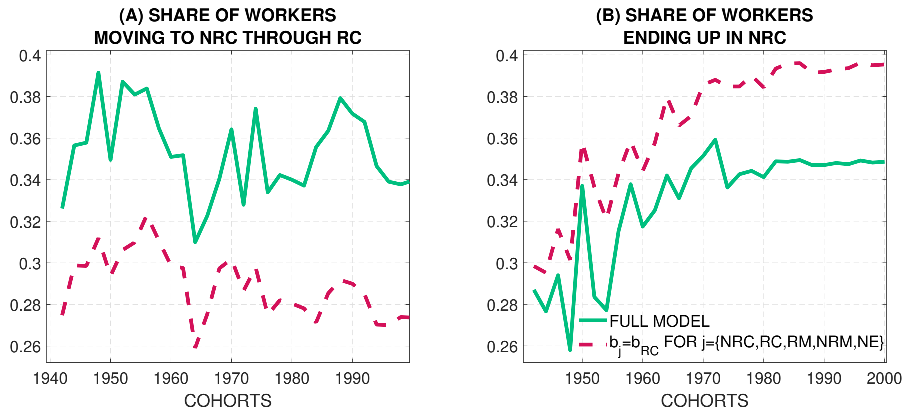

Figure 2.A7: Workers' transitions to NRC occupations by older age in full model and in the model with same human capital accumulation in all occupations

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.

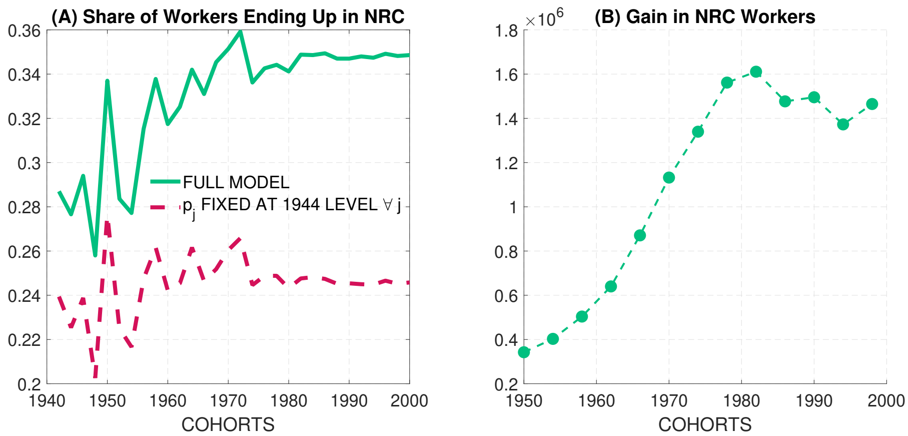

Figure 2.A8: Workers' transitions to NRC occupations by older age in full model and in the model with all arrival rates fixed at 1944 level

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).

Chapter 3

Ability to Adapt: from Biology to Labor Markets

3.1 Introduction

Existing papers in economics primarily focus on particular cases of labor market disruptions, such as automation (Acemoglu & Restrepo, 2020), offshoring (Firpo et al., 2011), and skill-biased technological change (Autor et al., 2003a). These disruptions, although significant in magnitude, are seen as affecting only specific parts of the skill/occupational distribution. For instance, research into automation focuses primarily on routine-intensive occupations as being the most susceptible to replacement by the machines (Goos & Manning, 2007a; Acemoglu & Autor, 2011a; Autor & Dorn, 2013a; Frey & Osborne, 2017; Acemoglu & Restrepo, 2018). Similarly, skill-biased technological change literature talks about benefits for high-skilled workers and how it contributes to the inequality between those high- and low-skilled (Heckman et al., 1998; Krusell et al., 2000; Autor et al., 2003a).

However, current and prospective labor market disruptions are likely to affect a much broader range of occupations, and all parts of the skill distribution. For example, artificial intelligence, including currently booming natural language processing tools such as ChatGPT, is expected to impact not only relatively low-skilled occupations, e.g., in customer support, but potentially also high-skilled and creative occupations[1,2] — the ones that were considered to be secured from the technological replacement.

Another source of current and prospective labor market disruptions is climate change. In addition to its apparent effects on agriculture and forestry, climate change, along with the growing probability of natural disasters, leads to massive local and international reallocation of labor force from the affected regions (McLeman & Smit, 2006; Missirian & Schlenker, 2017) to the areas with more favorable climate, but with potentially very different labor market conditions. As the climate change crisis develops and a wider range of societies becomes affected, all kinds of workforce, independent of their education, skill level, and occupations, will have to adapt to the changed local labor market environment or to move and adapt to other labor markets.

To comprehensively analyze and predict the consequences of ongoing and prospective labor market disruptions, a general theory of worker adaptation is needed. Taking into account a rich set of individual characteristics of workers, the theory must also be universal enough to predict adaptive responses across different contexts. Such a highly universal and predictive adaptation theory has already been developed in biology and ecology — sciences that have been studying the adaptation of the most diverse entities in the universe.

In this paper, I consider a state-of-the-art economic model of workers' decision making and use it to quantitatively evaluate the predictions of adaptation theory from modern biology and ecology in relation to changing labor market environments. The universality of the results delivered by many decades of adaptation research in biology and ecology allows me to analyze the adaptive responses of workers across different contexts within a single framework, to predict the consequences of major labor market disruptions, and, ultimately, to make a step towards the development of a general theory of worker adaptation.

The key predictions of adaptive theory in biology and ecology are stated as follows:

Prediction 1: *Environmental signatures define the modes of adaptation*.
Different variable environments favor different adaptive response modes. The key characteristics of the environment (*environmental signatures*) resulting in different adaptive responses are the timescale of environment variation, i.e., the frequency with which the

[1] businessinsider.com/chatgpt-jobs-at-risk-replacement-artificial-intelligence-ai-labor-trends-2023-02

[2] economist.com/graphic-detail/2023/04/14/chatgpt-could-replace-telemarketers-teachers-and-traders

environment (e.g., air temperature) is changing and the predictability of this variation (Simons, 2011; Botero et al., 2015; Tufto, 2015). For instance, organisms facing rapid but certain/predictable changes in the environment are likely to adapt through *activational (or reversible) plasticity*, i.e., by changing their plastic traits in different directions in response to environmental cues (Piersma & Drent, 2003; Piersma & Van Gils, 2011). At the same time, it has been shown that organisms facing slow changes in the environment towards some certain/predictable future state tend to adapt through *developmental (or irreversible) plasticity*, i.e, by altering their fundamental, less plastic traits that tend to be fixed over a lifetime (Moran, 1992; West-Eberhard, 2003; Cleland et al., 2007). When the environment is changing rapidly and in unpredictable ways, species minimize the variance of their adaptive outcomes by investing into different kinds of traits that can be useful under different scenarios, a so-called *bet-hedging* (Love et al., 2005; Crean & Marshall, 2009; Starrfelt & Kokko, 2012).

In economics, one of the main mechanisms of adaptation to changing labor market conditions is job switching, whereby workers choose jobs in accordance with their current comparative advantage (Autor & Dorn, 2013a; Cortes, 2016a; Cortes et al., 2017a; Jaimovich et al., 2021). In addition to job switching, workers' skills can be modelled as evolving gradually through learning-by-doing on their current jobs (Kambourov & Manovskii, 2009a; Yamaguchi, 2012b; Guvenen et al., 2020; Lise & Postel-Vinay, 2020; Taber & Vejlin, 2020). Workers can also respond to labor market shocks by investing directly into their productive characteristics (Heckman et al., 1998; Huggett et al., 2006; Lazear, 2009; Huggett et al., 2011; Cavounidis & Lang, 2020).

The economic model I develop and use in this paper features all of these adaptive responses. Workers choose the direction of their job search based on the amounts of cognitive, manual, and interpersonal skills they currently posses. Over time, the skills of workers are evolving through learning-by-doing, allowing workers to adapt to the skill requirements in the jobs that they currently hold. In addition to learning-by-doing, workers can build up their skills stock by directly investing into each of their skills. Through investment, workers can adapt faster to their current jobs, as well as to prepare themselves for prospective changes in skill requirements.

Calibrating the model to NLSY79 and O*NET data, I demonstrate that workers adapt differently to environments in which the job skill requirements are changing frequently, as opposed to environments in which the required skills are fixed over longer horizons. Moreover, workers exhibit different adaptive responses in environments in which they are certain about the skill requirements that they will be facing in future, as opposed to environments in which future skill requirements are random.

For skills such as cognitive, that are associated with large costs of mismatch and a high degree of skill-requirement complementarity, adaptive response modes follow the principles of bet-hedging, activational and developmental plasticity. In contrast to cognitive skill, manual skill can be accumulated rapidly, is not associated with the large costs of mismatch and does not produce distinct adaptive response modes, with adaptive responses for that skill changing continuously across environments. The slowest speed of accumulation and depreciation, together with the low costs of mismatch, render interpersonal skill virtually fixed over the lifetime of workers, and keep the adaptive responses of workers along this skill dimension at a negligible level compared to other skills.

As an application of adaptation results delivered by the model, I represent the major occupational categories as different labor market environments and map them into the adaptive response mode regions of cognitive skill predicted by the model. According to the mapping, workers in Management, Computer & Mathematical, Sales & Related occupations adapt to changing labor market environment through bet-hedging; workers in Production, Construction & Extraction occupations respond to changing skill requirements by activational plasticity; and Legal, Education & Library, and Community & Social Service workers' adaptation follows the principle of developmental plasticity.

Prediction 2: ***Transitions between environmental signatures are associated with tipping points***.

While significant variations in environmental signatures can be accommodated by existing adaptive responses, the adaptive capacity of individuals, populations, and even the sustainability of entire ecosystems can fall dramatically after a certain threshold (*tipping point*) is crossed in the variables that characterize the environment (Scheffer, 2010; Clark et al., 2013; Dakos et al., 2019). Transitions between different variable environments are difficult to adapt to when the transitions require the development of entirely new adaptive responses (Botero et al., 2015; Gunderson & Stillman, 2015; Boyd et al., 2016; Graae et al., 2018; Collins et al., 2020). Developing new adaptive responses often requires a significant amount of time and resources that are not always available, especially when the changes are rapid and unanticipated.

Having determined the adaptive responses for different skills of workers, I show that most changes in the labor market environment are not associated with significant changes in workers' lifetime outcomes. However, the transitions between the different adaptive response modes for cognitive skill cause significant losses in lifetime consumption, increase unemployment risks and, therefore, represent the potential tipping points.

I argue that automation shock represented a tipping point, associated with the transition of automated workers from activational plasticity to a bet-hedging adaptive response mode, i.e., to an environment with less predictable cognitive skill demands. In contrast, the introduction of AI has the potential to move workers from developmental and bet-hedging response modes to activational plasticity response mode. While workers undergoing such transitions are likely to adapt well to the developmental plasticity environment, AI may undermine the adaptive capacity of the future generations of workers who will be starting their careers on labor markets with fully fledged AI utilization. Additionally, I discuss that climate change affects both the frequency and the predictability of changes in labor market environment, with workers from Wholesale & Retail Trade, and Entertainment and Recreation Service industries being among the groups most vulnerable to increases in annual temperatures.

Prediction 3: ***Environment change forges adaptation, with bimodality in adaptive responses***.

Experienced environmental fluctuations are forging adaptive capacity by selecting individuals and species that are flexible, prone to behavioral innovation and learning (Wolf et al., 2008; Sayol et al., 2016; Sol et al., 2016; Wright et al., 2022). The globally observed pattern of adaptation is such that, under low environmental variability, the distribution of cognitive capacity of species that captures the flexibility and variety of possible adaptive responses is unimodal, with the most of the mass of the distribution concentrated around the medium levels of cognitive capacity. As environmental variability increases, medium cognitive capacity species start to disappear and are replaced by species with either low or high levels of cognitive capacity, i.e., the distribution becomes *bimodal* (Fristoe & Botero, 2019; Sayol et al., 2020). Low cognitive capacity species adapt by developing traits that allow them to sustain some minimal amount of well-being, independently of how unfavorable current environment conditions are (Pianka, 1970; Moss, 1983; Riek & Geiser, 2013; van Woerden et al., 2014). In contrast, high cognitive capacity species employ the highly flexible and versatile responses to benefit from varying environmental conditions (Sol et al., 2005, 2016; Ducatez et al., 2020).

The model in this paper predicts that the effect of experiencing environmental variation on workers' adaptive capacity is non-monotonic: the adaptive capacity of workers is forged in environments that are characterized by either high or low variability in skill requirements, while workers from intermediate skill variability environments find it difficult to adapt to changes. Moreover, greater variability of cognitive skill requirements leads to *bimodality* in the cognitive skill distribution. In highly variable environments, where investment into cognitive skill is associated with larger risks, it does not pay off to have intermediate levels of cognitive skill. Instead, depending on their initial skill endowment, workers exposed to high degrees of environment variation either build up large stocks of cognitive skill, equipping themselves for jobs with any cognitive skill requirement, or rely on manual and interpersonal skill, avoiding cognitive skill-intensive occupations.

I provide suggestive evidence of coexistence of low and high cognitive skill workers and a low share of intermediate skill workers in environments characterized by high degree of variability of cognitive skill requirements. I further relate the bimodality of the cognitive skill distribution with observed labor market polarization.

The rest of the paper proceeds as follows. Section 3.2 specifies the quantitative economic model of worker's decisions and formally defines the differences in labor market environments. Estimation of the model is discussed in Section 3.3. After assessing the fit and discussing parameter estimates, Section 3.4 uses the estimated model to test the predictions of adaptive biology and ecology in the context of changing labor market environments. Section 3.5 describes the sources of different labor market environments, maps major occupational categories to adaptive response modes produced by the model, and discusses bimodality in adaptive responses and the implications of major labor market disruptions within the model framework. Section 3.6 concludes.

3.2 Specification of Economic Model

Here, I describe the economic model that I use in the analysis of worker adaptation to changing labor market environments. I build the core of the model in the spirit of Lise & Postel-Vinay (2020) and extend it to account for the characteristics of environment considered to be key in adaptation theory in biology and ecology. Informing the economic model with adaptation theory from biology and ecology allows me to put structure on the analysis of the adaptive responses of workers across different labor market contexts and to obtain a fairly universal analytical and predictive framework of worker adaptation.

Workers. In the model, there are three skills representing different productive characteristics of workers and jobs: cognitive, manual, and interpersonal. A worker in the model is characterized by the stocks of cognitive, manual, and interpersonal skills that she possesses in each period of her lifetime:

$$S_a = [S_{c,a}, S_{m,a}, S_{i,a}] \ , \tag{3.1}$$

where a indexes the periods of the worker's lifetime, and c, m, i stand for cognitive, manual, and interpersonal skills, respectively.

Environment. In the setting of the labor market model, the environment faced by a worker is represented by the skill requirements of the jobs that the worker holds throughout her lifetime. A job that a worker holds in age a is characterized by the constant skill requirements on each of the worker's skills[3]:

$$R_a = [R_{c,a}, R_{m,a}, R_{i,a}]. \tag{3.2}$$

Jobs are different in the requirements that they place on each of the skills, and a worker not matching these skill requirements incurs the costs of being under-skilled or over-skilled.

Adaptation to the current environment. A worker is perfectly adapted to the current environment if $S_a = R_a$., i.e., if all her skills are equal to the skill requirements of her current job. The earnings of a worker with skill S_a holding a job with skill requirements R_a are given by the production function $f(S_a, R_a)$, defined in Equation 3.3:

$$f(R_a, S_a) = \alpha_T + \sum_{n=c,m,i} \alpha_n R_{n,a} - \kappa_n^u min\{S_{n,a} - R_{n,a}, 0\}^2 + \alpha_{nn} R_{n,a} S_{n,a}. \tag{3.3}$$

In this production function, $\alpha_n R_{n,a}$ terms stand for the unconditional returns to skill requirements characterizing the job and account for the fact that jobs with different intensities of skill use may have different productivity, independent of a worker's qualifications. Terms $\alpha_{nn} R_{n,a} S_{n,a}$, with $\alpha_{nn} \geq 0$, capture the degree of complementarity between a worker's skills and the corresponding skill requirements. α_T is the total factor

[3] In the model, a change in skill requirements is equivalent to job switching. While it is plausible that there can be changes in the skill requirements within the job, the characterization of a job as a fixed set of requirements is associated with data limitations discussed in the following sections.

productivity term.

In addition to linear skill requirement terms, the production function features mismatch terms $\kappa_n^u min\{S_{n,a} - R_{n,a}, 0\}^2$, in which $\kappa_n^u \geq 0$. These are the costs of being under-skilled, capturing the loss of output associated with a worker having insufficient skill relative to the skill requirements of her current job. The potential differences in the productivity costs from being under-skilled along different skill dimensions are captured by skill-specific coefficients κ_n^u. If a worker is under-skilled along skill dimension n, for a given job, the quadratic costs of being over-skilled are making the output of that worker concave in the amount of skill n. Once the skill of a worker reaches the respective skill requirement, the mismatch term for that skill becomes zero and the output of a worker becomes linear in the amount of skill, given that a worker keeps the same job.

Further, function $D(S_a, R_a)$ captures the utility cost that a worker suffers from holding a job for which one, or more, of her skills are exceeding those required by the job:

$$D(S_a, R_a) = \sum_{n=c,m,i} \kappa_n^o max\{S_{n,a} - R_{n,a}, 0\}^2 \quad , \tag{3.4}$$

where κ_n^o captures the potentially different costs of being over-skilled along each of the three skill dimensions[4]. Similarly to the productivity cost of being under-skilled, the utility cost of being over-skilled is non-zero only for the skill dimensions along which a worker has amounts of skill exceeding those required by the job.

The skills of a worker are evolving towards the current job requirements through *learning-by-doing.* As defined by Equation 3.5, over time, a worker's skills are gradually adjusting upwards if she is under-skilled relative to the skill requirement in the current job. A worker's skills are gradually adjusting downwards (depreciating) if she is over-skilled relative to the current job skill requirement. Coefficients γ_n^u and γ_n^o capture the speed of skill accumulation and depreciation, allowing for differences across skill dimensions.

$$S_{n,a+1} = S_{n,a} + I_{n,a} + \gamma_n^u \max\{R_{n,a} - S_{n,a}, 0\} + \gamma_n^o \min\{R_{n,a} - S_{n,a}, 0\}, \text{ where } n = \{c, m, i\}. \tag{3.5}$$

[4]Utility cost of being over-skilled is introduced for the comparability with the model of Lise & Postel-Vinay (2020), which also features such costs. It is also compatible with the approach towards adaptation modelling in biology and ecology where having amounts of a trait above the level required for the current environment can be at least as costly as having insufficient amounts of that trait. In the subsequent estimations of the model, the utility cost of being over-skilled turns out to be quantitatively much less important than the cost of being under-skilled.

Adaptation to changing environment. The environment that a worker faces is not fixed; it varies over the A periods of the worker's lifetime as the jobs held by the worker are changing. From the first to A–1 period, a worker solves the following dynamic problem:

$$
\begin{aligned}
V(S_a, R_a) = \max_{I_a, R'_{a+1}} \; & C_a - D(S_a, R_a) \\
& + \beta E[p^s(1-p^d)\max\{V(S_{a+1}, R_a), U(S_{a+1})\} \\
& + p^s p^d \max\{V(S_{a+1}, R_a), V(S_{a+1}, R_{a+1}), U(S_{a+1})\} \\
& + (1-p^s)p^d \max\{V(S_{a+1}, R_{a+1}), U(S_{a+1})\} \\
& + (1-p^s)(1-p^d)U(S_{a+1})] \;\; ,
\end{aligned}
\tag{3.6}
$$

where p^s is the probability of keeping the same job and p^d is the probability of getting an offer from a different job. $V(S_{a+1}, R_a)$ is the value of staying with the same job in the next period, while $V(S_{a+1}, R_{a+1})$ is the value of taking a new job with the realized skill requirements R_{a+1}, if an offer arrives. $U(S_{a+1})$ is the value of unemployment.

At the beginning of each period, a worker with skill S_a holding a job R_a from the previous period gets income $f(S_a, R_a)$ and makes two kinds of choices:

- **Job choice:** for each skill, a worker chooses the direction of job search R'_{a+1}. If she receives an offer from a different employer, the realized offered skill requirements will be:

$$R_{n,a+1} = \omega_{n,a+1} R'_{n,a+1}, \text{ where } \omega_{n,a+1} \sim N(\mu_n, \sigma_n^2) \text{ and } n = \{c, m, i\}, \tag{3.7}$$

  i.e., in each skill dimension, the realized skill requirement of the offered job is the product of the worker's chosen (preferred) skill and skill requirement shock, reflecting the fact that workers are not always able to get job offers that are perfectly aligned with their preferences[5].

- **Skill investment:** a worker also chooses the amounts $I_{n,a}$ that she will invest in each skill (Equation 3.5). Investment is subject to convex costs, reflecting the progressively increasing costs of a large one-period skill investment. A worker allocates

[5]The multiplicative nature of the shock is in line with the data discussed in the later sections. Workers with some of the highest lifetime average levels of skill requirements are also experiencing some of the largest variation in the requirements when switching jobs.

the current period output between consumption and skill investment:

$$C_a = f(R_a, S_a) - \sum_{n=c,m,i} I_n^\rho \ , \tag{3.8}$$

where ρ captures the convexity of the skills investment cost. Skill investment allows workers to adapt to current job skill requirements at a pace faster than that of the pure learning-by-doing and, importantly, to prepare for the prospective changes in skill requirements.

In addition to learning-by-doing, present in the Lise & Postel-Vinay (2020) model, job choice and skill investment represent two extra margins of worker adaptation to a changing labor market environment.

After job and skill investment choices are made, a worker consumes the remaining part of income and faces one of four possible environment realizations (summarized in Table 3.1). In cases I-II, a worker has an option to remain in the same environment by continuing in her current job. Additionally, in case II, a worker can choose to take a newly offered job if the realized requirements R_{a+1} are associated with higher future value than those of the current job. Unlike for the previous two cases, in cases III-IV a worker loses her current job and must face a new environment with new realized skill requirements, either immediately, as in case III, or after a spell of unemployment, as in case IV [6]. After choosing from the available options the one that brings the highest expected future value, a worker enters the next lifetime period.

Case Description	Case probability	Environment
I) Keeps same job, no offer	$p^s \cdot (1-p^d)$	Remains the same
II) Keeps same job, gets offer	$p^s \cdot p^d$	Remains the same or changes
III) No same job, gets offer	$(1-p^s) \cdot p^d$	Changes
IV) No same job, no offer	$(1-p^s) \cdot (1-p^d)$	Changes

Table 3.1: Cases for Environment Realizations in Each Period

Environmental signatures. The conceptual contribution of adaptation theory in biology and ecology lies in defining the key characteristics of variable environments. Two key environmental characteristics, timescale of environment variation and predictability

[6] In each case, there is an opportunity to enter unemployment, an environment with all-zero skill requirements, and to get a fixed unemployment benefit b.

(or control) over the environment, allow biologists and ecologists to put structure on the analysis of adaptive responses across a broad variety of contexts (Simons, 2011; Botero et al., 2015; Tufto, 2015). The distinct variable environments are represented through environmental signatures — the combinations of the timescale of environment variation and control over the environment. Following the approach to the characterization of changing environments in biology and ecology, adapting the concept of environmental signatures to the economic context, I use these two variables to characterize changing labor market environments:

- **Timescale of environment variation** is the frequency with which workers are changing their jobs. Workers in seasonal jobs, e.g., in the tourist-oriented hospitality sector or seasonal construction, are facing shorter timescales, while workers with long-term contracts, e.g., tenured professors or engineers, are facing longer timescales.

  In the model, the differences in timescale across workers are introduced through different lifetime realizations of p^s and p^d, i.e., the probabilities of keeping the same job and of getting an offer from a different job. The timescale of environment variation increases with increasing $p^s(1 - p^d)$, whereby job switches appear less often and current job requirements persist for longer.
- **Control over the job choice** is the precision with which workers can choose their future jobs and the associated skill requirements. Among other things, control over the job choice, in a reduced form, may represent efficiency of employer-employee matching, labor market thickness, and rapid demand changes in a particular industry, as well as in the whole economy.

  The differences in control over the job choice are introduced into the model through different lifetime realizations of the variances of shocks to skill requirements $\omega_{n,a}$. Control over the job choice increases as the variance of $\omega_{n,a}$ (i.e., σ_n^2) falls, resulting in the offered skill requirements $R_{n,a}$ aligning more closely with those chosen by the worker $R'_{n,a}$. Maximum control over job choice ($\sigma_n^2 \to 0 \ \forall \ n$) corresponds to perfectly predictable skill requirements in the next period, whereas minimum control implies skill requirements on the jobs offered to a worker being idiosyncratic to the worker's skills.

Changes in the timescale of environment variation and the control over the job choice affect workers' optimal choices they make when facing a particular environment and may result in the appearance of distinct adaptive response modes. For instance, at higher levels of control over the job choice, i.e., in environments characterized by low σ_n^2, workers will choose jobs with higher requirements for the skills they possess in larger amounts, to benefit from potentially high skill-requirement complementarity (driven by parameter α_{nn} in the production function). Production function in Equation 3.3 is linear in the amount of a worker's skill, unless the worker is under-skilled. However, at higher levels of control over the job choice, the worker will choose jobs with progressively higher skill requirements for the skills associated with large α_{nn}, resulting in the lifetime output being convex in the amount of a respective skill. The convexity of a worker's output in skills when she can choose her skill requirements (weights) is one of the main implications of work by Lazear (2009) and Cavounidis & Lang (2020). In the context of this model, it creates incentives for more intensive skill investment at higher levels of control over the job choice.

On the other hand, at some of the lowest levels of control over the job choice, where workers essentially cannot choose the skill requirements with which they end up in the following periods, skill investment may have a precautionary motive when productivity costs of a mismatch κ_n^u are high. Skill investment effectively hedges a worker against large variations in earnings associated with the cases when the realized skill requirement $R_{n,a+1}$ is significantly above $S_{n,a+1}$.

With respect to the changes in the timescale of environment variation, on average, workers facing higher timescales are expected to invest more in skills, especially in those associated with larger costs of being under-skilled. Due to higher p^s (or lower p^d), the current skill requirements are likely to persist for many periods and, therefore, workers have incentives to invest in order to close the gap between current skill requirements and their, potentially insufficient, skill stock. The investment at longer timescales is also more intensive for skills for which the speed of learning-by-doing γ_n^u is low. Workers at lower timescales have fewer incentives to invest in skills, and the changes in their productive characteristics, resulting primarily from the frequent changes of skill requirements, are driven by learning-by-doing and depreciation of their skills.

In the following sections, I estimate the model described above and use it to test the presence of systematic differences in the ways workers adapt to different labor market environments. Establishing the presence of such systematic differences makes it possible to put structure on the analysis of workers' adaptation and to predict the adaptive capacity of workers in the face of current and prospective labor market environment changes.

3.3 Estimation

Model parametrization and simulation. I simulate the model specified in the previous section monthly for a cohort of 20,000 individuals who are drawing their initial skills vector from a distribution estimated on the data discussed below. I simulate each worker for 25 years (300 months), with the calibration procedure targeting the first 15 years of workers' lifetimes.

Besides the initial skills, workers are also heterogeneous in the realizations of the labor market environments that they are facing throughout their lifetime. Specifically, across individuals, there are differences in the environmental signatures, i.e., in the combinations of the timescale of environment variation and control over the job choice. For the timescale of environment variation, the probability of keeping the same employer p^s and the probability of getting an offer from a different employer p^d, which are defining the frequency of skill requirement changes, are represented by the three-point distributions. Each worker may get either low, medium, or high realizations of the respective probabilities. The share of workers with a particular realization of p^s or p^d is:

$$P(p^k = p_l) = P_l^k, \text{ where } l \in \{low, med, high\} \text{ and } k \in \{d, s\}. \tag{3.9}$$

Similarly, for the control over the job choice, the distributions of variances of shocks to skill requirements σ_n^2 are:

$$P(\sigma_n^2 = \sigma_{n,l}^2) = P_{n,l}, \text{ where } l \in \{low, med, high\} \text{ and } n \in \{c, m, i\}. \tag{3.10}$$

Overall, with respect to the realizations of environmental signatures, there are 3^5 types of workers in the model. The realizations of different parameters of environment are independent. In the baseline simulations, each worker remains within the same environmental signature throughout their lifetime.

Skills investment cost parameter ρ is set equal to 2, mirroring the quadratic cost of mismatch. Discount rate β is set to 0.9918, to imply the monthly equivalent of 10% annual interest rate. In the model simulations, shocks to skill requirements are allowed to correlate, following the joint normal distribution. Additionally, the offer arrival rate for the unemployed, denoted p^{uo}, is estimated separately from the offer arrival rate for employed p^d and is set to be fixed across environments[7].

To get policy functions for skills investment and job choice, the worker's problem is solved backwards for each realization of worker type, using the combination of endogenous grid and finite difference methods. It is assumed that workers do not internalize the possible correlations between skill requirements when making their job choice. This assumption speeds up the solution process, by making the choice of a particular skill requirement dependent only on the current amount of the respective skill possessed by a worker[8]. Workers are informed about the parameters of the environment that they are facing and form rational expectations about the future realizations of current job separation, job offer arrivals, and the realizations of skill requirements.

Data used in the model. Moments used as targets in the model estimation and the distribution of initial skills are calculated on the data from Lise & Postel-Vinay (2020), combining individual-level weekly arrays for males from the main sample of NLSY79 with occupation-level data from O*NET. The data follows each worker from the NLSY79 sample on a month-to-month basis, from the moment of exiting full-time education until the first time a worker falls into unemployment for more than 18 months, and assigns job skill requirements calculated using O*NET data to each worker for whom a job is observed in a given month. The changes in skill requirements appear when a worker switches jobs[9]. While detailed descriptions about the data construction are provided in Lise & Postel-Vinay (2020), Table 3.2 shows some descriptive statistics for the variables related to initial skills and skill requirements faced by workers at different points of their lifetime (Panel A), and, especially, the variables which can be informative about the labor market environments experienced by different workers (Panel B).

[7]The alternative would be to have p^d fixed and p^{uo} changing across environments. Having both rates changing across environments would increase the state space beyond what can be feasibly computed and simulated.

[8]To test the strictness of this assumption, I run smaller versions of the model where I allow workers to internalize the correlations. Simulations of these models, with up to 20 periods, different discount rates and probabilities of offer arrivals, imply that the cross-derivatives of value functions with respect to different skill requirements are rather flat, as compared to the effects of skill mismatch along each particular skill dimension.

[9]While, potentially, there can be a within-job skill requirement variation over time, the currently used O*NET data allows only for the estimation of between-job variation in the required skills. In principle, the previous releases of data on the jobs skill content, such as the Dictionary of Occupational Titles (DOT) data, could be used to estimate the trends in the within-job skill requirements changes. However, due to the different sets of job descriptors included into DOT and the current version of O*NET, a reliable estimation of such trends is challenging.

The comparison of sample means with standard deviations in Panel B of Table 3.2 shows there is a large variation in the number of job switches and in the number of times in unemployment that workers experience in the course of their lifetime. This variation in turn points to potentially large differences in the timescale of labor market environment variation across workers. For example, workers who are one standard deviation below the mean of job switch distribution are switching jobs 1-2 times over 15 years, and are, therefore, facing largely stable skill requirements. At the same time, workers who are one standard deviation above the mean of job switch distribution are switching jobs 1-2 times per year.

Table 3.2: Descriptive Statistics for Data Used in Model Estimation

Panel A: Skills and Skill Requirements

	Initial Skills		Skill Requirements by Experience Levels: 1 year		5 years		15 years	
	mean	st.dev.	mean	st.dev.	mean	st.dev.	mean	st.dev.
Cognitive	0.57	0.21	0.36	0.17	0.41	0.17	0.45	0.16
Manual	0.60	0.16	0.53	0.19	0.55	0.18	0.57	0.18
Interpersonal	0.51	0.17	0.36	0.19	0.40	0.20	0.44	0.20
Observations	1773		1320		1416		1279	

Panel B: Labor Market Environments

Number of Job Switches		Times in Unemployment			St.Dev. of Skill Requirements	
mean	st.dev.	mean	st.dev.		mean	st.dev.
				Cognitive	0.07	0.05
10.96	9.39	2.24	2.55	Manual	0.08	0.06
				Interpersonal	0.08	0.06

Note: Standard deviations of skill requirements, numbers of job switches, and times in unemployment statistics are calculated for each individual in the sample from the moment of exiting full-time education until the first time a worker falls into unemployment for more than 18 months and for the maximum of 15 years into the sample. For Panel A, standard deviations are calculated for a cross-section of workers of particular age. For Panel B, standard deviations are calculated over the whole period that each worker spends in the sample.

Furthermore, there are substantial differences in the variation in skill requirements faced by workers over their lifetime. Workers who are one standard deviation above the mean of the distribution of lifetime variation in cognitive skill requirements are facing 6 times higher variation in skill requirements than those who are one standard deviation below the mean of the distribution. Differences in lifetime skill requirement variation for manual and interpersonal skills are even more pronounced.

A part of these differences, not explained by the frequency of job switches[10], skill accumulation, and career progression, is attributed to variation in control over the job choice — a labor market environment characteristic capturing how precisely a worker can choose skill requirements of the offered jobs. In later sections, I discuss the sources of such differences in control over the job choice, as well as in the timescale of labor market environment variation, including location, education groups, occupational categories and industries where workers spend most of their working lifetime.

Targeted moments and identification. The remaining parameters of the model are estimated using the method of simulated moments. The optimization procedure chooses a vector of model parameters to minimize the squared Euclidean distance between the data moments and the corresponding moments delivered by the model simulations. The optimization procedure combines the pattern search method, to find the rough estimates of the model parameters, with the simplex search method, to fine-tune the parameter vector obtained from pattern search.

Targets used in the model estimation procedure are calculated using the data described above and can be divided into two sets, based on the types of model parameters for which these targets are the most relevant.

Skills and skill requirements targets include the moments used in Lise & Postel-Vinay (2020). Specifically, in order to discipline the parameters associated with productivity, skill accumulation, and the costs of mismatch, the estimation procedure targets: (i) coefficients of descriptive regression of log wages on initial skills, skill requirements of jobs held, tenure, and experience; (ii) mean unemployment-to-employment (U2E) rate; (iii) mean lifetime profile of the rate of employer-to-employer (E2E) switching; (iv) mean profiles of job skill requirements; (v) standard deviation profiles of job skill requirements; (vi) correlation profiles of job skill requirements; and (vii) correlation profiles of initial skills and job skill requirements.

[10]Later in the paper, I also show that the frequent job switches are not necessarily associated with the largest variations in skill requirements.

While the model parameters are identified jointly to provide the best fit to the targeted moments, some of the empirical targets are especially informative about the particular parameter values. For instance, matching the coefficients on the the initial skills and their interactions with skill requirements from log-wage regression informs the values of skill return parameters α_n and α_{nn}. Correlation profiles of initial workers' skills with job skill requirements inform the model about the significance of mismatch costs along each of the skill dimensions, reflected in κ_n^u and κ_n^o parameters. The same correlation profiles, together with the mean profiles of skill requirements, identify the rates of skills accumulation through learning-by-doing γ_n^u and of skills depreciation γ_n^o.

The offer arrival rate for unemployed workers p^{uo}, as well as the mean offer arrival rate for those employed, are pinned down by U2E and E2E profiles. Standard deviation profiles of job attributes help to inform the means of control over the job choice distributions. Targeting the correlation profiles of job skill requirements ensures that workers are holding jobs with realistic skill requirement combinations and makes it possible to identify correlations in the joint distribution of shocks to skill requirements. Means of the shocks distribution are informed by mean profiles of skill requirements.

Additionally, I use *environmental targets* to discipline the parameters responsible for the distribution of environmental signatures (i.e., the combinations of timescale and control over the job choice) among workers in the NLSY79 data[11]. Distributions of probabilities of keeping the same employer p^s and getting an offer from different employer p^d are informed by environmental targets including the distributions (standard deviations, skewness, and kurtosis) of (i) the number of times in unemployment over the lifetime and (ii) the number of employer switches over the lifetime. Furthermore, distributions of σ_n^2 are informed by the distributions of (iii) the standard deviations of cognitive, manual, and interpersonal skill requirements over the lifetime.

To account for the fact that there might be correlations between the initial characteristics of a worker and the subsequent labor market environment faced by that worker, the targeted distributions are calculated using the residuals from the regressions of a particular statistic controlling for the amounts of initial skills and the level of education.

[11]It should be mentioned that environmental targets are not purely *environmental* in the sense that they represent a combination of workers' choices and the shocks that they are experiencing over lifetime and that are exogenous to the model. The estimated model matches the environmental targets with the combination of endogenous choices of workers, disciplined by skills and skill requirement targets, and the exogenous idiosyncratic shocks. Variation in these idiosyncratic shocks is associated with the variation in timescale and control over the job choice representing different labor market environments.

Table 3.3 summarizes the results of such regressions for all five variables that can be informative about the variation in labor market environments, along with their residual distributions used as targets in the model estimation. Regression results, for instance, suggest a statistically significant negative correlation between the initial amounts of cognitive and interpersonal skills and the frequencies of job switching and unemployment transitions over the lifetime. In contrast, the larger amounts of manual skill are positively correlated with the frequency of job switching. By focusing on the variation in the labor market environment that is orthogonal to the initial workers' characteristics, the model aims to compare workers from different skill groups and to observe the potential differences in their adaptation to the same labor market conditions.

Table 3.3: Initial Conditions Regressions

	Number of Job Switches	Times in Unemployment	St. Dev. of Skill Requirements: Cognitive	Manual	Interpersonal
	(1)	(2)	(3)	(4)	(5)
S_{c0}	-1.42***	-0.21***	-0.03**	-0.10***	-0.03
	(0.29)	(0.08)	(0.02)	(0.02)	(0.02)
S_{m0}	0.88***	0.09	0.03**	0.07***	0.03*
	(0.23)	(0.06)	(0.01)	(0.02)	(0.02)
S_{i0}	-0.44***	-0.11***	-0.01	-0.01	0.01
	(0.15)	(0.04)	(0.01)	(0.01)	(0.01)
Highest Educ.	-0.01	-0.01**	-0.00	0.00	0.00
Grade	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
Constant	1.78***	0.53***	0.08***	0.09***	0.06***
	(0.24)	(0.07)	(0.01)	(0.02)	(0.02)
Observations	1696	1770	1750	1750	1750
Adjusted R^2	0.11	0.10	0.02	0.07	0.00
Distributions of Residuals:					
St. Dev.	0.87	0.24	0.05	0.06	0.06
Skewness	1.13	1.34	0.70	0.60	0.75
Kurtosis	4.39	5.10	3.50	3.21	3.07

Note: Robust standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

For the lifetime profiles of workers' characteristics and the associated job attributes, the estimation procedure directly targets each 30th month over the period of the first 15 years of workers' labor market participation. Together with the coefficients of descriptive wage regression, 6 such profiles give 44 skills and skill requirements targets. In addition, there are 15 environmental targets associated with the distribution of environmental signatures across workers. In total, this gives 59 data moments to be targeted by the model with 51 estimated parameters[12].

3.4 Results

3.4.1 Model Fit and Estimated Parameters

Figures 3.1 and 3.2 demonstrate the fit of the calibrated model. From Figure 3.1, the simulations of the calibrated model produce the average U2E rate and E2E rate profiles and the profiles of mean and standard deviation of job requirements reasonably close to those calculated based on the NLSY79 and O*NET data. Importantly, the model simulations reproduce fairly well the correlations of job and worker attributes, identifying the parameters of the learning-by-doing functions and the costs of skill-requirement mismatch. Pairwise correlations of the job requirements, i.e., the moments identifying the set of skill requirement combinations available to workers, are also closely matched.

Further, from Figure 3.2, the coefficients of the descriptive wage regression fall within the 95 percent confidence bands of the corresponding coefficient estimates from the empirical wage regression. The correspondence between the model-based and data-based descriptive wage regression coefficients ensures the adequacy of the estimated returns to job skill requirements.

The remaining panels of Figure 3.2 demonstrate the fit of the model to the moments responsible for the identification of different environmental signatures among workers. The standard deviations, skewness, and kurtosis of the residuals from the regression of the number of times in unemployment and the number of employer switches over the lifetime help to pin down the distributions of the probability of keeping the same employer in the next period and of the probability of getting an offer from a different employer in the next period — the two distributions responsible for the differences in the timescale of environment variation across workers. The distributions of the residuals from the regressions of standard deviations of the skill requirements over the workers' lifetimes on the workers' initial skills and education pin down the distribution of the variances

[12] For the three-point distributions of the labor market environment, only the low and the high realizations are estimated independently. The medium realizations are taken as the averages of low and high values.

of shocks to the chosen skill requirements — the source of variation in control over the job choice in the next period. While the standard deviations are mostly well reproduced by the estimated model, the fit for higher moments could be improved by increasing the number of points with which the distributions of environmental parameters are estimated.

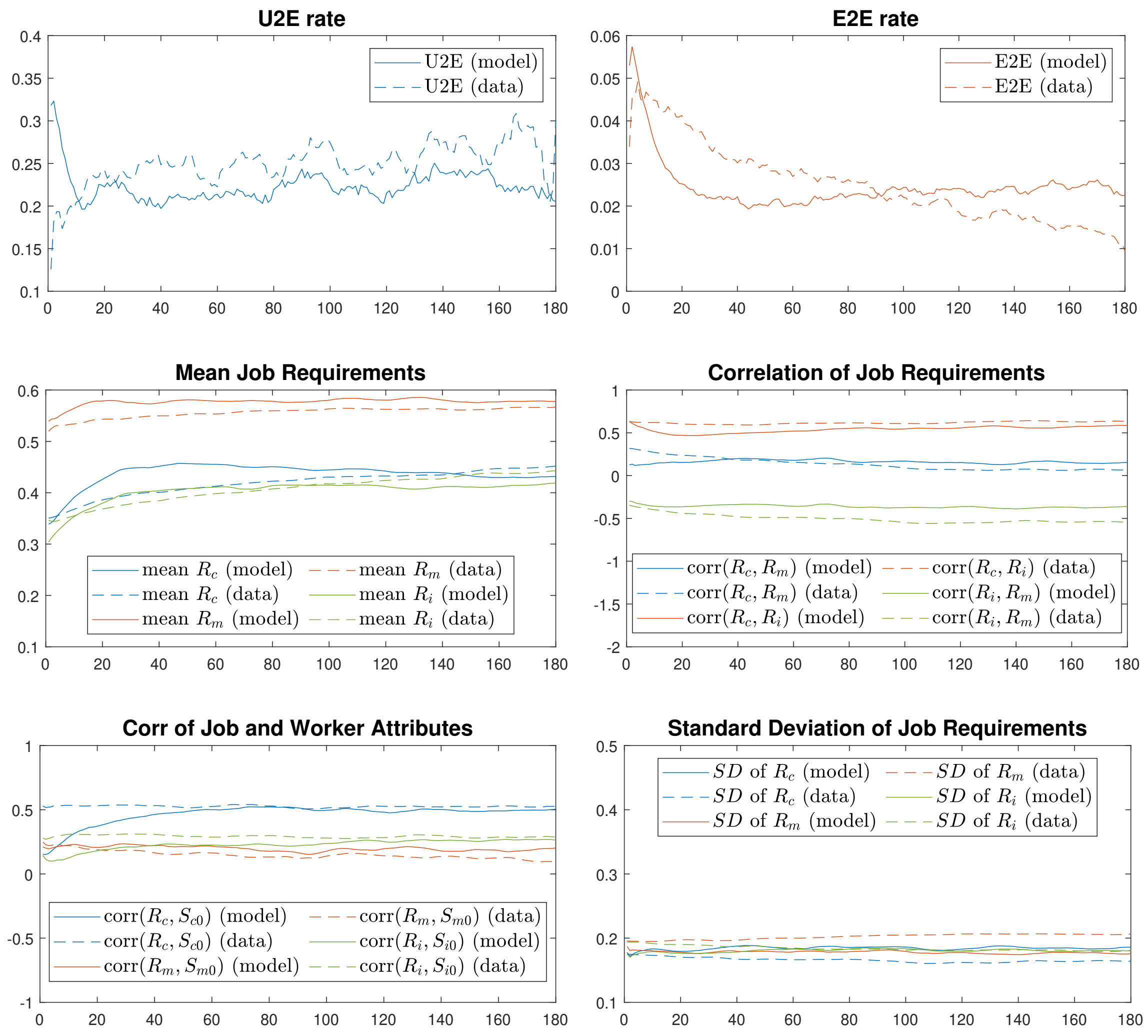

Figure 3.1: Model Fit — Skills and Skill Requirements Targets, First 15 Years (180 Months) of Workers' Lifetimes

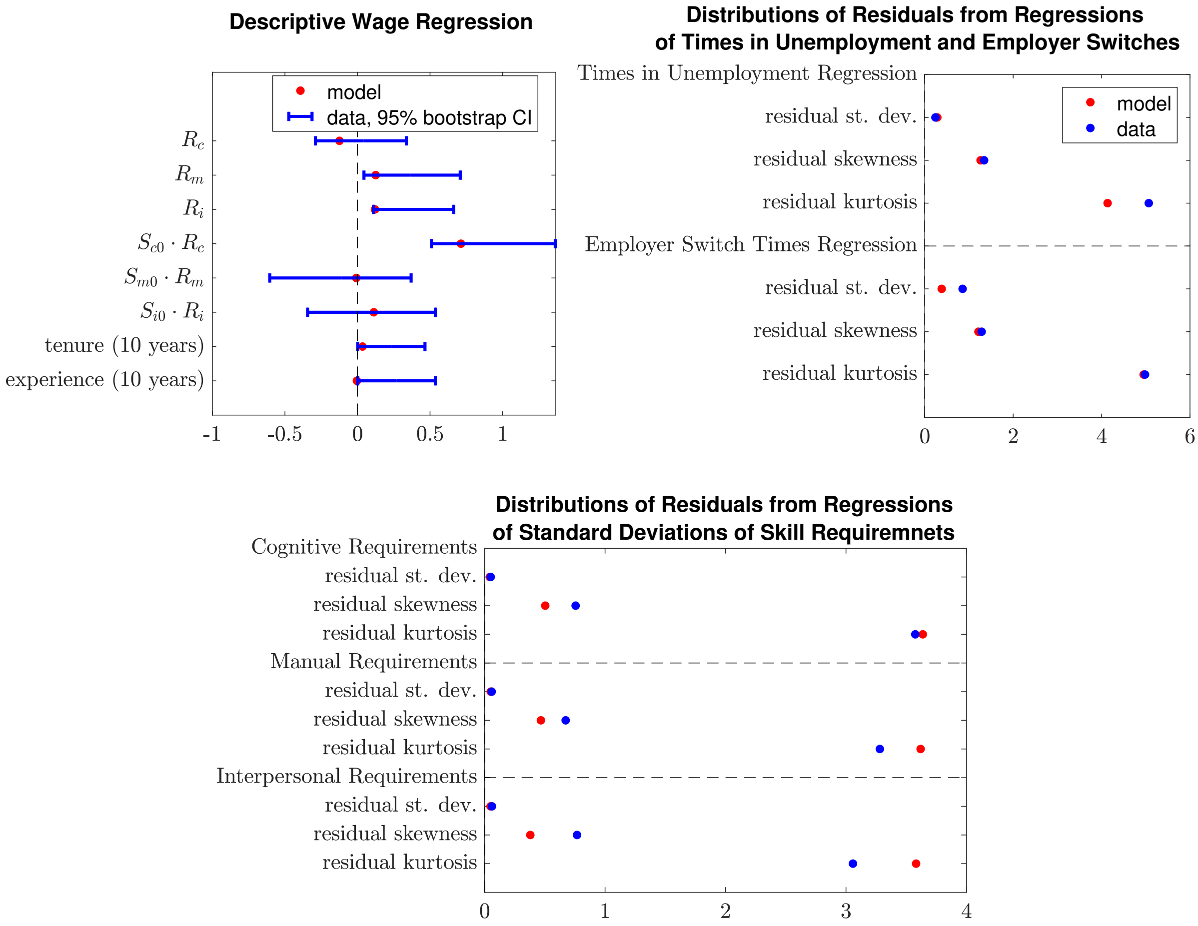

Figure 3.2: Model Fit — Wage Regression and Environmental Targets

Table 3.4 summarizes the estimated model parameters. The baseline productivity of jobs is increasing in skill requirements. The highest unconditional returns to skill requirements are observed for interpersonal skill (α_i). At the same time, while cognitive skill brings the lowest unconditional returns to the job requirements (α_c), this skill is also characterized by the highest degree of complementarity between the worker's skill and the corresponding job skill requirement (α_{cc}).

Further, the most severe costs of mismatch appear among workers under-qualified along the cognitive skill dimension (κ_c^u). Manual skill is the one that can be accumulated through learning-by-doing with the highest speed (γ_m^u is the largest). The depreciation of cognitive and manual skills occurs at comparable speeds (γ_c^o vs. γ_m^o). However, for interpersonal skill, both depreciation (γ_i^o) and accumulation through learning-by-doing (γ_i^u) are occurring at the pace slowest among the three skills.

Table 3.4: Parameters of the Estimated Model

Panel (A)

Production Function: Returns to Job Skill Requirements

α_T	α_c	α_m	α_i	α_{cc}	α_{mm}	α_{ii}
145.31	5	50	80	200	0	15
Production Function: Costs of Mismatch				**Disutility of Work**		
κ_c^u	κ_m^u	κ_i^u		κ_c^o	κ_m^o	κ_i^o
1,500	100	80		130	50	100
		Skill Accumulation				
γ_c^u	γ_c^o	γ_m^u	γ_m^o	γ_i^u	γ_i^o	ρ
7.7e-3	4.5e-3	5.4e-2	2.0e-3	1.0e-3	5.6e-6	2
Un. Ben.	**Disc. Fac.**	**Offer Prob., Un.**				
b	β	p^{uo}				
137.5	0.9918	0.39				

Panel (B)

Environmental Variables: Timescale

Probability of Keeping Same Employer				Offer Probability from Different Employer			
p^s	0.90	0.94	0.99	p^d	0.1	0.2	0.3
Share (P^s)	0.01	0.28	0.71	Share (P^d)	0.22	0.04	0.74

Environmental Variables: Control over Job Choice

Variance of Cognitive Skill Requirements				Variance of Manual Skill Requirements				Variance of Interpersonal Skill Requirements			
σ_c^2	0.20	0.25	0.30	σ_m^2	0.20	0.25	0.30	σ_i^2	0.15	0.23	0.30
Share (P_c)	0.04	0.37	0.59	Share (P_m)	0.04	0.37	0.59	Share (P_i)	0.04	0.37	0.59

Other Parameters of Skill Requirement Shocks Distribution (Multivariate Normal)

μ_c	μ_m	μ_i	$corr_{cm}$	$corr_{ci}$	$corr_{im}$
0.5	0.82	0.5	0.14	0.73	-0.44

Turning to the estimates of the distributions of the environments among workers, the probability of keeping the same employer in the next period p^s is between 0.9 and 0.99, with the largest share of workers having high probability of remaining with the same employer (P^s_{high}). The probability of getting an offer from a different employer p^d is from 0.1 to 0.3 in every period, with the shares of workers having low and high probabilities of getting an offer (P^d_{low} and P^d_{high}) being larger than the share of those with medium realization (P^d_{med}). The distributions of the variances of skill requirements are virtually the same among the three skills, which arises from fairly similar distributions of the residuals from the regressions of the standard deviations of skill requirements.

To get a better picture of the types of workers/labor market environments present in the estimated model, Figure 3.3 shows the distribution of workers across timescale variables and control over the choice of cognitive skill requirement. Larger squares represent different offer arrival probabilities, while smaller squares are the grid of environments with different degrees of control over the job choice along the cognitive skill dimension and the probability of remaining with the same employer representing different environmental signatures[13]. Control over the job choice is increasing as the variance of shock to cognitive skill requirements σ_c^2 is decreasing, with $\sigma^2_{c,high}$ corresponding to a low level of control over the job choice along the cognitive skill dimension.

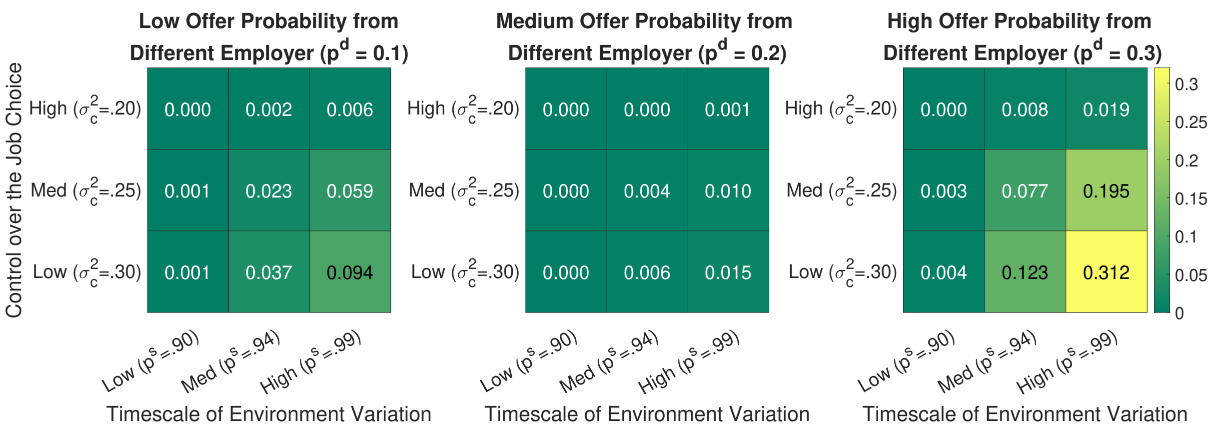

Figure 3.3: Distribution of Workers' Types

Note: This figure shows the distribution of workers in the estimated model across labor market environments, conditional on a particular combination of variances of manual and interpersonal skill requirements shocks. The sum of shares in all squares adds up to 1.

[13]In the sections to follow, the differences in the timescale of environment variation will be represented through changing p^s, holding the probability of offer arrival at its mean level.

As suggested by Figure 3.3, the largest share of workers are facing a long timescale of labor market environment variation. Model estimations also imply a substantial share of workers with low and medium realizations of control over the job choice along the cognitive skill dimension, with the workers having high control constituting a minority at all timescales.

3.4.2 Adaptive Responses of Workers

I now use the estimated model to establish how workers adapt to the labor market environments characterized by: (1) different timescales of the skill requirements variation, and (2) different control over the skill requirement choice. To this end, I simulate a sample of 5,000 workers with their initial skills set to the means of the estimated initial skill distribution on the grid of environmental signatures identified in the course of the calibration. For each of the three skills, I simulate the sample of workers under different values of the variance of the shock to the corresponding skill requirement σ_n^2 , i.e., control over the job choice, and different probabilities of keeping the same employer in the next period p^s , i.e., the timescale.

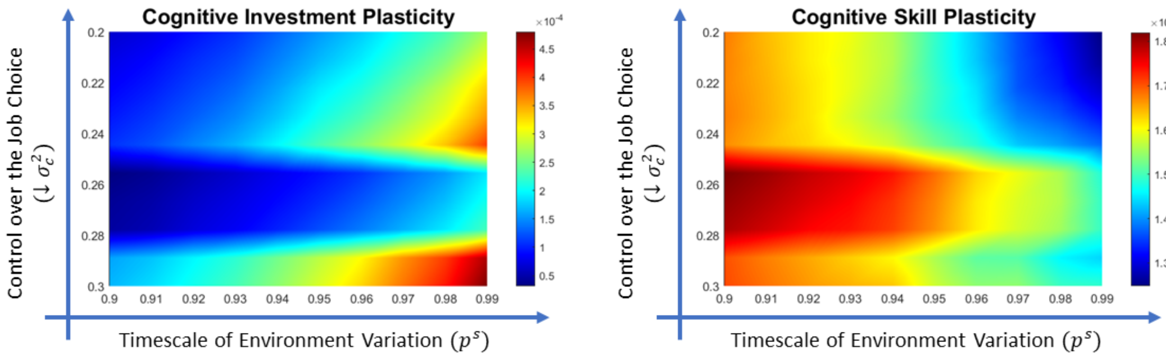

Figure 3.4: Adaptation of Workers — Cognitive Skill

Note: The figure shows the adaptive responses of workers along the cognitive skill dimension across different environmental signatures (i.e., different combinations of timescale of environment variation and control over the cognitive skill requirements). Adaptive responses are calculated as of the 30th month into the life cycle of workers. The earlier date in the worker life cycle is chosen to show the investment responses, which die out later in a lifetime. When simulating different levels of control over the cognitive skill requirement, the controls over the other two skill requirements are fixed at their respective means.

For workers from different environments, I calculate two measures of adaptive responses. The first, skill plasticity, is calculated as the absolute change in the stock of skill between periods. The second, investment plasticity, is simply the amount of investment into a particular skill in each period.

Two panels of Figure 3.4 show the adaptive responses of workers to different timescales and levels of control over the job choice along the cognitive skill dimension. For the labor market environments with different levels of control over the job choice, the three adaptive modes, corresponding to *bet-hedging, activational* and *developmental plasticity*, can be distinguished. The distinct response modes for cognitive skill appear due to high costs of being under-skilled κ_c^u and high skill-requirement complementarity α_{cc}.

As is evident from the left panel of Figure 3.4, the most intensive investment in cognitive skill occurs in labor market environments characterized by either very little to no control over the job choice, or in environments with high levels of control. For low-control environments, costly investment in cognitive skill pays off due to the extremely high productivity costs from being under-skilled along the cognitive skill dimension. The cognitive skill investment has a *bet-hedging* motive — changes of jobs with significant variation in the cognitive skill requirement, make workers to augment their stock of cognitive skill in order to decrease the variance of their earnings and of their resulting consumption.

In environments with a high degree of control over the job choice, workers can choose the cognitive skill requirements closely aligned with their skills. Facing a highly predictable demand for cognitive skills, workers are building up their skill stock over their lifetime to enable them to choose jobs that are more intensive in cognitive skill and to benefit from a high degree of complementarity between cognitive skill requirement and their cognitive skill stock. In other words, workers are developing their initial skill in order to benefit from predictable environment, i.e., workers are adapting through *developmental* plasticity.

At intermediate levels of control, however, workers' investment into cognitive skill is less intensive. At the same time, as is illustrated in the right panel of Figure 3.4, intermediate levels of control over the cognitive skill requirements are associated with the highest level of cognitive skill plasticity. In such environments, workers still do not have much control over the cognitive skill requirements in the offered jobs, but the skill mismatch is less critical on average than it is at the lowest levels of control for the workers to bet-hedge by investing into cognitive skill. On the other hand, control over the job choice is not high enough for workers to build up their cognitive skill over their lifetime through costly investment, i.e., to adapt through developmental plasticity. Instead, workers allow their skills to adjust to current skill requirements through learning by doing and depreciation. This adaptation mode can be attributed to *activational* plasticity: with every new job, cognitive skill is either adjusting upwards or downwards, depending on the workers being under-skilled or over-skilled.

Table 3.5: Characteristics of Adaptive Response Modes for Cognitive Skill

	I_c growth timesc. (%/month)	Cumul.I_c after 5y. (% of $S_{c,0}$)	S_c growth timesc. (%/month)	Cumul.$\lvert\Delta S_c\rvert$ after 5y. (% of $S_{c,0}$)	Cumul.ΔS_c after 5y. (% of $S_{c,0}$)	Mean S_c after 15y. (% of $S_{c,0}$)
Dev. plast.	7.4	1.8	0.3	15.0	-10.9	75.5
Act. plast.	9.2	1.1	0.2	16.3	-14.0	70.5
Bet-hedg.	6.1	2.8	0.3	15.8	-7.8	80.8

Note: The table compares the characteristics of different adaptive response modes produced by the model. The first and third columns show the average growth rate of cognitive skill investment and cognitive skill stock when the timescale of environment variation increases by one month. The second, fourth, and fifth columns show the cumulative investment, absolute, and net cumulative changes in the cognitive skill stock after 5 years on labor market as a percentage of the initial skill stock. The last column shows the mean stock of cognitive skill after 15 years on labor market as a percentage of initial skill stock.

Table 3.5 further summarizes the properties of the response modes implied by model estimation. The first column shows that the amount of investment in cognitive skill is increasing in the timescale across all three response modes. On average, with each additional month of stable environment, investment in cognitive skill increases by 7.6 %. At the higher timescales, workers have to invest in cognitive skill to close the gap between the current cognitive skill requirement, which is likely to persist for many periods due to higher p^s, and their own, often insufficient, stock of cognitive skill. While aiming to close the gap between their skills and persistent skill requirements, workers still undergo occasional job changes and, on average, lag behind the current environment (are mismatched with their cognitive skill).

For all three response modes, the average net change in the stock of cognitive skill (column 5 of Table 3.5) is negative. Average cognitive skill depreciation is associated with high costs of being under-skilled and the mean of the shock to cognitive skill requirements being below one. At the same time, the rates of skill stock growth in column 3 suggest that an average worker has to stay with the same employer for as long as 24 months for the worker's cognitive skill to start growing.

Turning to the differences between the adaptive response modes, from the second column of Table 3.5, bet-hedging is associated with the most active accumulation of skill through investment, 2.5 times more intensive than under activational plasticity. On the other hand, the activational plasticity mode is characterized by the largest magnitudes of absolute and net skill plasticity (columns 4-5 of Table 3.5). Due to low investment, a decrease in cognitive skill for this adaptive response mode is by 6.8 and 3.1 percentage point larger than for bet-hedging and developmental plasticity respectively. The largest decrease in the stock of cognitive skill for activational plasticity also reflects on the mean of skill at later stages of working lifetime (column 6 of Table 3.5).

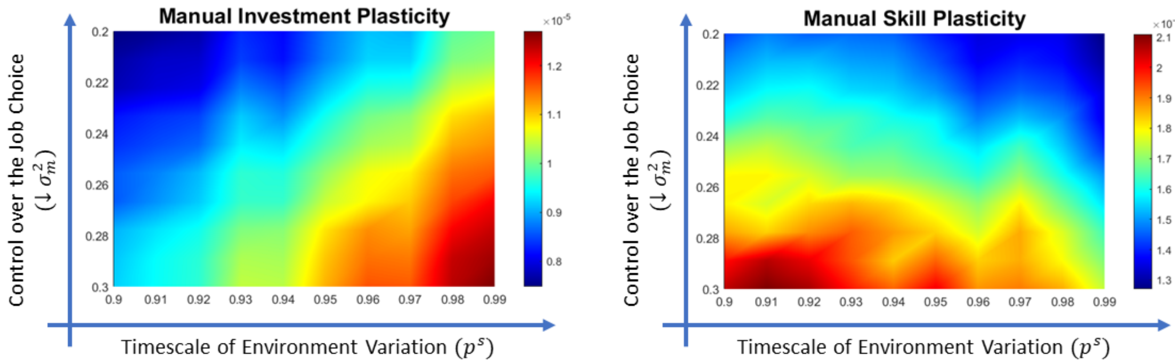

Figure 3.5: Adaptation of Workers — Manual Skill

Note: The figure shows the adaptive responses of workers along the manual skill dimension across different environmental signatures (i.e., different combinations of timescale of environment variation and control over manual skill requirements). For further details, see the note under Figure 3.4.

Figure 3.5 shows adaptive responses for manual skill. Unlike for cognitive skill, manual skill responses change continuously over environments characterized by different timescales and control over the manual skill requirement. The absence of distinct response modes is due to manual skill being associated with low costs of mismatch (κ_m^o, κ_m^u), high speed of learning-by-doing (γ_m^u), and virtually absent skill-requirement complementarity (α_{mm}).

Similarly to cognitive skill, manual skill investment is also increasing with the timescale, but at a lower rate: on average, after 5 years on the labor market, each additional month of a stable job environment is associated with a 2.4 % increase in cumulative manual skill investment. Also, Figure 3.5 shows that manual skill investment plasticity is at least an order of magnitude lower than that of cognitive skill. Due to the low costs of mismatch, workers have low incentives to invest into manual skill at low levels of control over the job choice. Investment at higher levels of control does not pay off due to low skill-requirement complementarity.

High levels of skill plasticity in environments in which workers have low control over the manual skill requirement are associated with rapid accumulation of manual skill by workers employed in occupations in which requirements do not match their skill (accumulation through learning-by-doing). On average, a 1% increase in the variance of a shock to the manual skill requirements is associated with a 2.4% increase in manual skill plasticity. The largest mean manual skill stocks are therefore observed at the lowest control levels where manual skill plasticity is also the highest. At higher levels of control, workers adapt by choosing jobs with manual skill requirements more closely aligned with their current skill stock, which does not leave much space for learning-by-doing and results in lower mean manual skill levels, as compared to environments in which control over the job choice is lower.

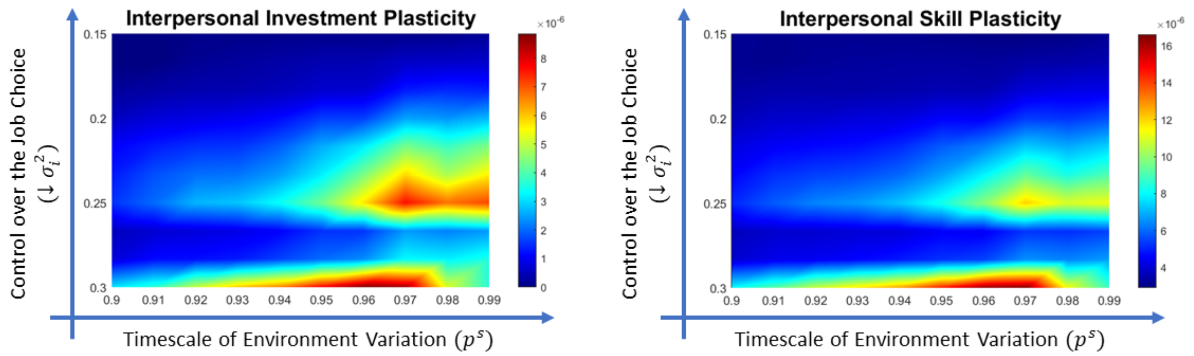

Figure 3.6: Adaptation of Workers — Interpersonal Skill

Note: The figure shows the adaptive responses of workers along the interpersonal skill dimension across different environmental signatures (i.e., different combinations of timescales of environment variation and control over the interpersonal skill requirements). For further details, see the note under Figure 3.4.

As for interpersonal skill (Figure 3.6), the slow pace of its accumulation and depreciation (γ_i^o, γ_i^u) render it virtually fixed over lifetime of workers. Low costs of mismatch (κ_i^o, κ_i^u), comparable to those for manual skill, and low skill-requirement complementarity (α_{ii}) also do not create incentives for investment in it — investment in interpersonal skill is less than in manual skill and is negligible compared to investment in cognitive skill. The small variation present in interpersonal skill and investment plasticity is driven by the strong positive correlation with cognitive skill.

3.4.3 Transitions Between Environments

Now, as the patterns of the adaptive responses across different environmental signatures have been established for each skill, I proceed to assess the consequences of transitioning between environments for workers of different age. I compute the average remaining lifetime consumption and unemployment risk for workers who undergo an unanticipated transition to a different labor market environment at a particular moment in their lifetime, and compare it to the average consumption and unemployment risk for workers who were in that different environment from the beginning of their lifetime.

Figures 3.7 and 3.8 illustrate the consequences of transitions between environments characterized by different timescales of job requirement variation and control over the choice of cognitive and manual skill requirements. Each panel of Figures 3.7-3.8 is composed of 100 tiles representing a particular combination of control over the job choice and the timescale of environment variation. In turn, each tile is divided into four trapezoids. The position of a trapezoid within a tile and its color represent the transition into a particular adjacent target environment and the consequences of such transition for workers. Specifically, the upper trapezoids in each tile represent a one-step increase in control over the job choice at a given point of a lifetime, while the lower trapezoid in a tile represents a one-step decrease in control over the job choice. Similarly, left and right trapezoids in a tile show the transitions associated with decreases and increases in the timescale. All the transitions are always to the adjacent environments.

The trapezoids in shades of red signify a decrease in average remaining lifetime consumption or an increase in unemployment risk over the remaining lifetime for workers who transitioned to the target environment, relative to workers who were in that target environment for their whole lifetime. Blue trapezoids show increases in consumption and decreases in unemployment risk for transitioning workers, relative to those working in the target environment from the start. The intensities of the colors indicate the magnitudes of changes in consumption and unemployment risk.

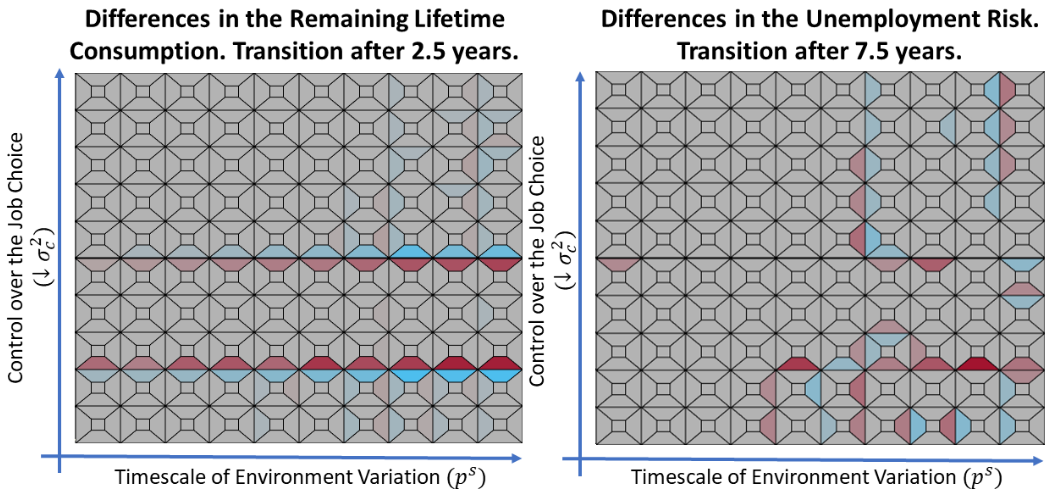

Figure 3.7: Transitions Between Environments: Cognitive Skill

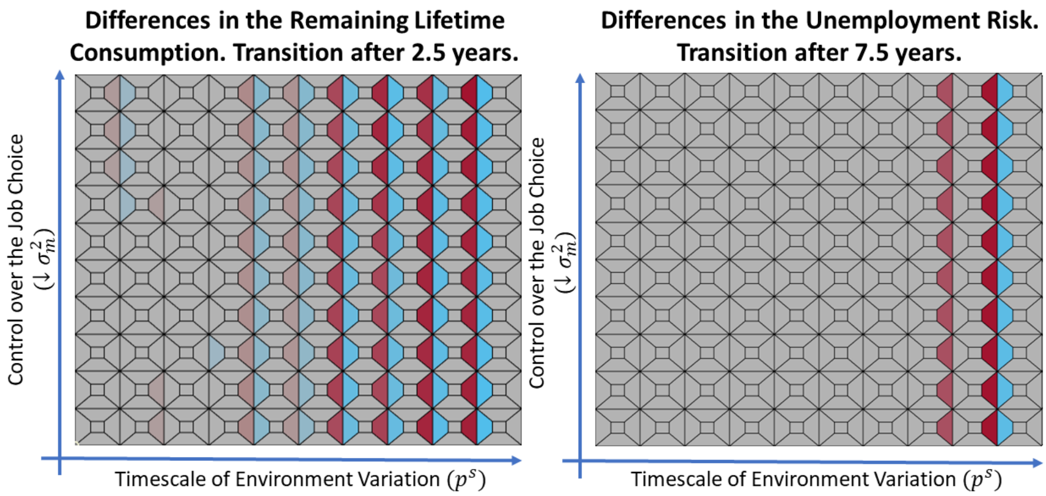

Figure 3.8: Transitions Between Environments: Manual Skill

Note: The panels of Figures 3.7-3.8 show the consequences of transitions between labor market environments characterized by different environmental signatures. Each panel is composed of 100 tiles. Each tile represents a particular environmental signature and is divided into four trapezoids signifying one-step transitions to the adjacent environmental signatures. E.g., the upper trapezoids in each tile signify a one-step increase in control over the job choice, while right trapezoids show a one-step increase in the timescale. The red/blue trapezoids identify transitions after which workers' outcomes are worse/better than the respective outcomes of the workers who started their lifetime in that environment. The intensities of the colors indicate the magnitudes of differences in the average outcomes of the transitioning workers and the workers who worked in that environment from the beginning of their lifetime. For all panels, p^s is from 0.9 to 0.99, σ_n^2 is from 0.2 to 0.3

As is evident from Figure 3.7, for cognitive skill, most of transitions between environmental signatures are not associated with significant changes in remaining lifetime consumption and unemployment risk. However, transitions between the three response mode regions defined by different levels of control over job choice are likely to cause sizable consequences. The left panel of Figure 3.7 shows that younger workers from regions with intermediate levels of control over cognitive skill requirement are likely to experience a significant decrease in their relative remaining lifetime consumption when they transition to environments characterized by higher and lower levels of control. These transitions therefore represent potential *tipping points*.

Changes in the adaptive response modes identified in Figure 3.4 underlie losses in consumption. Moving to the lower levels of control, the workers who were previously adapting through activational plasticity have to either increase their cognitive skill investment or experience large losses of productivity in times when they have to accept jobs that require a lot of cognitive skill. In both cases, this reflects on the amounts available for consumption. From Table 3.6, workers transitioning from activational plasticity to the bet-hedging region after 5 years on the labor market experience up to 7.5% loss in post-transition lifetime consumption and up to a 5.1% increase in unemployment risk, relative to the workers native to the bet-hedging environment. As the workers grow older, their propensity to invest into skills is decreasing, while the differences in mean cognitive skill between the environments are accumulating. Therefore, the effect of transitioning from activational plasticity to the bet-hedging region after 15 years on labor market are much more substantial: up to a 24% loss in post-transition lifetime consumption and up to a 21% increase in the unemployment risk.

Further, transitions to the higher levels of control require workers from intermediate control environments to invest actively into their cognitive skill to to catch up with the workers who were adapting through developmental plasticity from the beginning of their lifetimes. The necessity to invest into cognitive skill and overall lower productivity leaves the workers transitioning from activational plasticity environments after 5 years on the labor market with 6.5% less lifetime consumption and 2.2% higher risk of unemployment. For older workers, the effect of the transition is amplified: up to a 43% of loss in the remaining lifetime consumption and up to a 13% increase in their risk of unemployment.

Additionally, for older workers (right panel of Figure 3.7) the transitions characterized by the largest losses in consumption and increases in unemployment risk are mainly concentrated around the areas of the most intensive investment in cognitive skill and are driven by the lower propensity of older workers to invest in their skills.

Table 3.6: Effects of Transitions between Adaptive Response Modes

	Transition after 5y.		Transition after 15y.	
	Lifetime Cons.	Unemp. Risk	Lifetime Cons.	Unemp. Risk
Avg. abs. difference	0.7	0.3	2.4	1.6
Act.plast.→Dev.plast.	$[-6.5, -0.4]$	$[+0.3, +2.2]$	$[-43, -3.4]$	$[+0.2, +13]$
Act.plast.→Bet-hedg.	$[-7.5, -0.0]$	$[+0.0, +5.1]$	$[-24, -3.4]$	$[+0.0, +21]$
Dev.plast.→Act.plast.	$[+0.7, +5.6]$	$[-4.8, -0.0]$	$[+1.7, +12]$	$[-13, -0.1]$
Bet-hedg.→Act.plast.	$[+0.0, +8.6]$	$[-7.0, -0.0]$	$[+0.0, +14]$	$[-14, -0.0]$

Note: Lifetime consumption columns show the difference in post-transition lifetime consumption of transitioning workers compared to workers native to the target environment. The unemployment risk columns show the difference in post-transition unemployment risk compared to the unemployment risk of native workers. Average absolute differences are computed across all possible one-step transitions. All values are in percentages of the native population values.

Notably, reverse transitions, i.e., transitions towards the environment favoring activational plasticity, are associated with increases in relative consumption and decreases in unemployment risk, for both younger and older workers (lines 4 and 5 of Table 3.6). This is due to the fact the the costs of being over-skilled are relatively low and workers with larger stocks of cognitive skill transitioning from low- or high-control environments are on average more productive than workers native to the intermediate control environment.

Turning to manual skill, from Figure 3.8, the transitions between environments with different control over the manual skill requirement are not associated with significant changes in consumption and unemployment risks. This is because manual skill can be rapidly accumulated through learning-by-doing and the mismatch productivity loss for manual skill is not as large as for cognitive skill. At the same time, transitions along the timescale axis are accompanied by the changes in the lifetime consumption and unemployment risk. These changes are driven by different intensities with which workers at different timescales are investing into their cognitive skill. Figure 3.1 shows that cognitive skill investment is increasing non-linearly at longer timescales across all control levels, with the workers transitioning from lower timescales having disproportionately lower stocks of cognitive skill than workers who were on that longer timescale from the start of their working lifetime.

3.4.4 Cognitive Skill Distribution in Variable Environments

Figure 3.9 demonstrates the distributions of cognitive skill by the end of the sample period for different labor market environments. The shape of the distribution varies across the environments. At higher levels of control over job choice, the distributions are unimodal, showing higher skewness on higher timescales. Overall, for higher control environments, cognitive skill distribution is concentrated between the low and intermediate levels of skill. As control over the cognitive skill requirement is decreasing, the mass of intermediate cognitive skill workers starts to decrease, and the mass of workers with lower and higher cognitive skills increases. In other words, under the lower levels of job choice control, the cognitive skill distribution is becoming *bimodal*: there are a lot of workers with low and high levels of cognitive skill and there is a low share of intermediate skill workers.

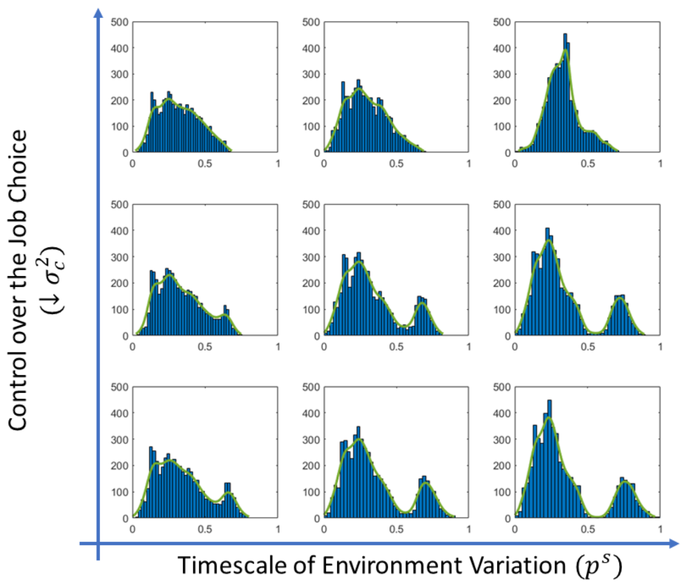

Figure 3.9: Distribution of Cognitive Skill, 180th Month

Note: From top to bottom, distributions in rows are calculated for σ_c^2 equal to 0.25, 0.3, and 0.4. From left to right, distributions in columns are calculated for p^s equal to 0.9, 0.95, 0.99. I obtain the distributions from simulating the lifetime paths of 10,000 workers from the initial skill distribution estimated on the NLSY79 data. For all environments, control over manual and interpersonal skill are fixed at their respective means. The green lines represent the kernel density estimates.

Over the lifetime, workers in the lower job choice control environments experience larger variations in cognitive skill requirements. Under the high costs of cognitive skill mismatch and with the most of the returns to cognitive skill coming from the complementarity between the cognitive skill requirement and the worker's own cognitive skill, only workers with a large initial skill stock choose the cognitive-skill-intensive occupations. They also actively invest in their cognitive skill. At the same time, workers with lower cognitive skill endowment cannot benefit much from the skill complementarity and sort to occupations with lower cognitive skill intensity to avoid high productivity losses. While they may still invest some amounts into cognitive skill for bet-hedging purposes, on average such workers end up in jobs with lower cognitive skill requirements and, hence, have few opportunities for learning-by-doing along this skill dimension. Additionally, workers with lower cognitive skill endowment more often fall into unemployment, where their cognitive skill rapidly depreciates. Intensive accumulation of cognitive skill by workers with high initial skill endowment on the one hand, and the sorting of low initial endowment workers into the occupations not requiring much of cognitive skill on the other hand, generates cognitive skill bimodality in the environments with higher levels of cognitive skill variation.

Unlike in the environments with low control over the job choice, workers in higher control environments can choose jobs that are more closely aligned with their skill and, therefore, can afford staying with the intermediate levels of cognitive skill. Distributions similar to the high control distribution of cognitive skill are observed for interpersonal skill in different control and timescale environments (Figure 3.2). Virtual constancy of interpersonal skill distribution is due to the low pace of its accumulation/depreciation and lower costs of mismatch than with cognitive skill. The distribution of manual skill (Figure 3.3) does not change much across the environments with different control over the cognitive skill requirement. However, more manual skill is accumulated by workers in the lower timescale environments. This more active accumulation of manual skill in more rapidly changing environments is due to the high mean level of variation in the manual skill requirement.

3.5 Discussion

3.5.1 Sources of Differences in Labor Market Environments

In Section 3.4.2, I establish the presence of distinct adaptive responses for the environments characterized by different timescales and control over the job choice. Now I investigate the sources of differences in the environmental signatures: what represents different labor market environments for workers.

On a within-country level, some natural candidates for different labor market environments would be different industries, labor markets for different educational groups, and occupational categories to which workers belong throughout a significant part of their lifetimes. Figure 3.10 compares the average standard deviation of cognitive skill over a lifetime (used as the source of variation for identification of control over the cognitive skill choice in the model) across different occupational categories of the NLSY79 cohorts. As the figure shows, workers who spent most of their lifetime in Legal occupations experience two times lower variability in cognitive skill requirements compared to workers in Personal Care & Service occupations. Notably, the differences in cognitive skill requirement variability are not fully explained by the cognitive skill intensity of the occupations. For instance, Architecture & Engineering occupations, which are highly intensive in cognitive skill, show the highest levels of cognitive skill variability, along with some occupations that are less demanding in terms of cognitive skill, e.g., Healthcare Support.

For the number of job switches over a worker's lifetime, a variable that largely identifies the timescales of the environmental variation in the model, the two panels of Figure 3.11 show significant differences across industries and the labor markets for different educational groups. Workers employed in Entertainment & Recreation Services, Mining, and Construction industries experience up to three times more job switches over their lifetimes, compared to those employed in Financial, Insurance, & Real Estate, Public Administration, and Professional & Related Services industries. Differences of similar magnitudes are observed for workers on labor markets for different educational groups, where the number of switches correlates negatively with years of education.[14]

Overall, all five variables used for the identification of different labor market environments in the model show some degree of variation across occupations, industries, and educational groups (Figures 3.4-3.11 in the Appendix). There are significant differences between occupational categories and industries in terms of the number of times workers fall into unemployment and switch jobs over their lifetime. For instance, on average, workers who spend most of their lifetime in Mining and Construction industries experience unemployment 10 times more often than workers from Personal Services industry. Similarly to the number of job switches, the number of times in unemployment, as well as the standard deviations of all skill requirements over the lifetime, are lower for workers

[14]This relationship reverses when I control for other characteristics of workers in the regressions that are discussed below.

holding bachelor's and higher degrees.

Notably, low variability along one of the skill dimensions does not necessarily imply low variability along the other skill dimensions. For instance, Community & Social services are characterized by one of the lowest standard deviations of cognitive and manual skill requirements, while the standard deviation of interpersonal skill requirements in this occupational category is one of the highest. Likewise, Protective Services, with one of the lowest standard deviations of cognitive skill requirement, are among the occupations characterized by higher standard deviations of interpersonal and manual skill requirements.

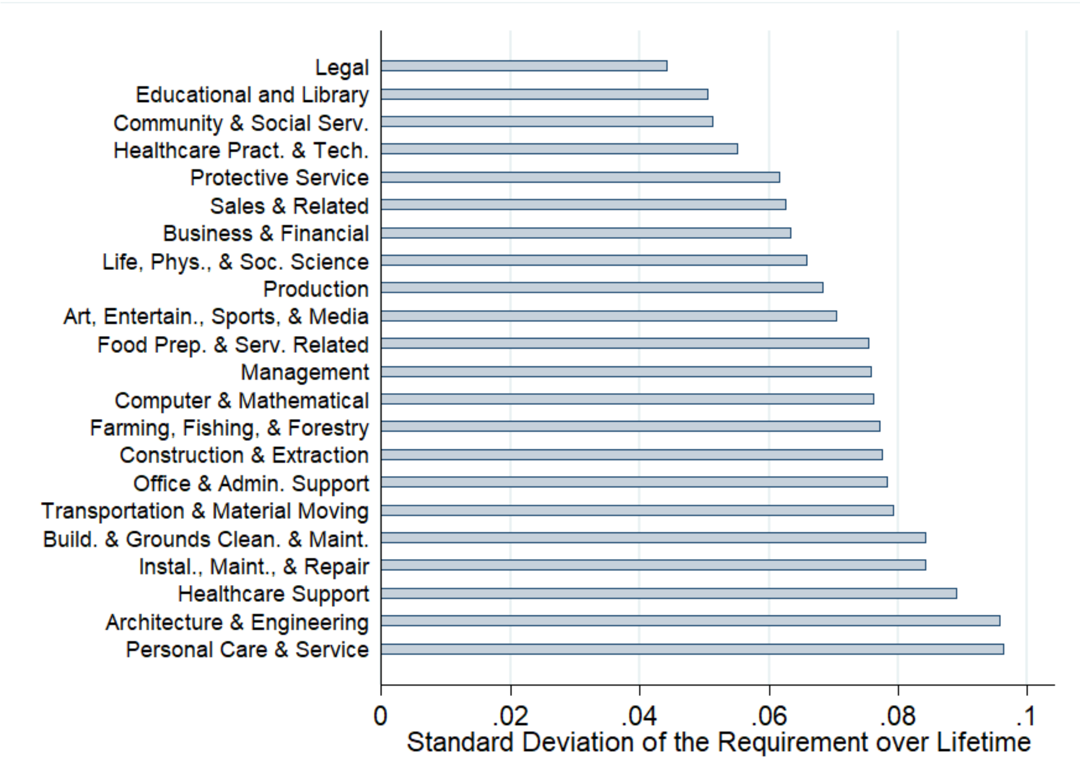

Figure 3.10: Standard Deviation of Cognitive Skill by Major Occupational Categories
Note: Standard deviations of the skill requirements are calculated over the lifetimes of individuals from the NLSY79 data, with changes in the skill requirements identified at the moments of job switching. Individuals are assigned to different categories based on the occupations in which they spent the largest number of months over their lifetimes.

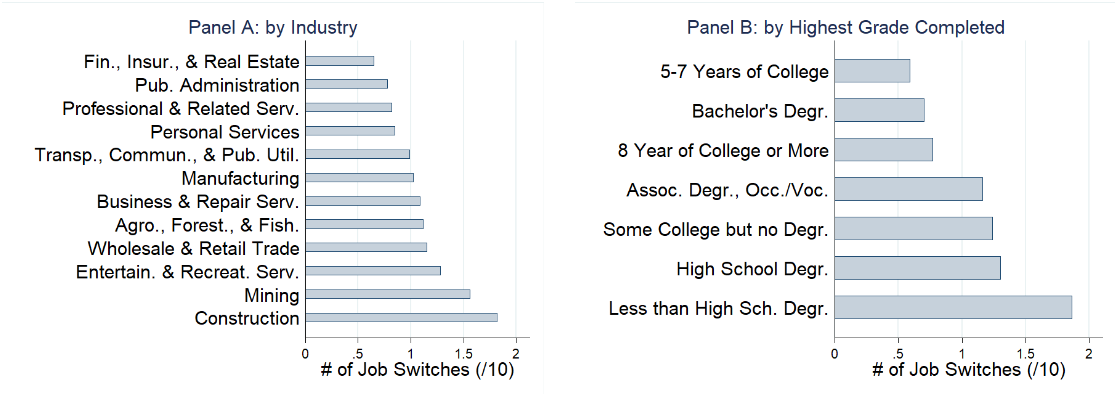

Figure 3.11: Number of Job Switches Over the Lifetime

Note: Number of job switches over the lifetime is calculated using the weekly arrays of NLSY79 data. For Panel A, individuals are assigned to different categories based on the industry in which they spent the largest number of months over their lifetimes. For Panel B, individuals are assigned to different categories based on the highest level of education they have achieved by the end of the observation period.

From a more general perspective, based on the model specification, any factor that affects the variability of skill requirements and the frequency of their change through the channels different from the initial skills endowment can be attributed to the characteristics of the worker's environment. Table 3.7 shows the results of regressions of the standard deviation of cognitive skill over the lifetime of workers on workers' initial skills and a set of variables which can be potentially treated as determinants of the workers' environments. In addition to the number of job switches, which by construction explains a share of variation in the standard deviation of cognitive skill requirement, the largest share of the explained variation in the cognitive skill standard deviation arises from the differences in workers' occupational categories. Likewise, for manual and interpersonal skill, occupational categories are responsible for a large share of explained variation in the standard deviations of the requirements (Tables 3.A2 and 3.A3). Among the other factors associated with statistically different variability in cognitive, manual, and interpersonal skill requirements are the number of years spent as a member of a labor union (decreases variability for all skills), residence in central cities of Standard Metropolitan Statistical Areas (increases variability for cognitive skill), and the number of years with reported health limitations (increases variability for interpersonal skill).

Table 3.8 shows estimates of the regressions for the number of job switches over the lifetime. Similarly to the skill requirements, occupational categories are informative about the number of job switches, as well as the number of times a worker may fall into unemployment (Figure 3.A1). In addition to years spent in labor union, place of residence, and health limitations, factors including marital status (less frequent switches and unemployment), US citizenship (less frequent unemployment), and being imprisoned (more frequent switches and unemployment) are of statistical significance.

Table 3.7: Correlates of the Standard Deviation of Cognitive Skill Requirement

	(1)	(2)	(3)	(4)	(5)
S_{C0}	-0.07**	-0.03	-0.05**	-0.05**	-0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
S_{M0}	0.03	0.02	0.03	0.03	0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
S_{I0}	-0.01	0.00	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years in labor union					-0.0002***
					(0.0000)
Years with health limitations					-0.0000
					(0.0000)
Lives in SMSA, central city					0.01**
					(0.01)
US Citizen as of 1984					-0.01
					(0.01)
Constant	0.09***	0.07***	0.11***	0.10***	0.11***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Controls for max. eudcational degree	✓	✓	✓	✓	✓
Controls for # of job switches and average skill requirments		✓	✓	✓	✓
Controls for 1st and 2nd most frequent occupation			✓	✓	✓
Controls for 1st and 2nd most frequent industry				✓	✓
Observations	1210	1210	1210	1210	1210
Adjusted R^2	0.03	0.19	0.29	0.30	0.31

Note: The table shows the results of the regression of the standard deviation of cognitive skill over the lifetime of workers from NLSY79 data on a set of explanatory variables. Controls for educational degree, occupations, and industries include controls for all categories in Figures 3.10-3.11. Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.8: Correlates of the Number of Job Switches over the Lifetime

	(1)	(2)	(3)	(4)
S_{C0}	-1.53***	-0.69	-0.56	-0.42
	(0.47)	(0.47)	(0.47)	(0.47)
S_{M0}	0.82**	0.43	0.36	0.32
	(0.39)	(0.39)	(0.39)	(0.38)
S_{I0}	-0.40**	-0.26	-0.27	-0.24
	(0.18)	(0.17)	(0.17)	(0.17)
Years in labor union				0.002*
				(0.001)
Years with health limitations				0.01***
				(0.00)
Lives in SMSA, not central city				-0.12*
				(0.06)
US Citizen as of 1984				-0.10
				(0.18)
Married most of lifetime				-0.19***
				(0.05)
Ever in jail				0.40***
				(0.13)
Constant	2.16***	1.34***	1.67***	1.88***
	(0.12)	(0.18)	(0.27)	(0.31)
Controls for max. eudcational degree	✓	✓	✓	✓
Controls for 1st and 2nd most frequent occupation		✓	✓	✓
Controls for 1st and 2nd most frequent industry			✓	✓
Observations	1326	1326	1326	1326
Adjusted R^2	0.14	0.24	0.25	0.29

Note: The table shows the results of the regression of the number of job switches over the lifetime for workers from NLSY79 data on a set of explanatory variables. Controls for educational degree, occupations, and industries include controls for all categories in Figures 3.10-3.11. Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

It should be noted that a large share of variation, e.g., in regressions in Tables 3.7 and 3.8, remains unexplained. A significant part of variation in workers' environments likely comes from local labor markets, i.e., commuting zones. However, identification of particular commuting zones or of counties is not possible with standard access to NLSY79 data.

3.5.2 Occupational Environments, Adaptive Responses, and Bimodality

Occupational categories account for a large share of explained variation both in the standard deviations of skill requirements over the lifetime of workers and in the number of switches between jobs, employment, and unemployment. In this section, I interpret different labor market environments as different occupations in which the workers are employed throughout most of their lifetime and map the occupational categories into the cognitive skill response mode regions produced by the calibrated model.

I use the estimated regressions summarized in Tables 3.7-3.8 to predict the standard deviations of cognitive skill requirements and the number of job switches over the lifetime of workers with mean initial skills employed in different occupational categories. Table 3.A4 shows predicted values of standard deviations of cognitive skill and the number of switches over the lifetime for 22 major occupational categories. The estimated regressions predict the largest variability of cognitive skill for occupations in Architecture & Engineering, Healthcare Support, Building & Grounds Cleaning & Maintenance, Personal Care & Service and the lowest for Education and Library, Legal, and Community & Social Service occupations. These predictions are generally in line with the average standard deviations of cognitive skill calculated across occupational categories in the previous section (Figure 3.10). Standard deviations of cognitive skill requirements and the number of job switches are not perfectly correlated. For instance, Management, with above-average variability in cognitive skill requirements, is among the occupational categories with the fewest predicted job switches over a lifetime. Food Preparation & Serving Related occupations have a standard deviation of cognitive skill close to that in Management, but are also characterized by one of the highest number of job switches over the lifetime. Although managers switch jobs less often, the changes in their cognitive skill requirements are larger than for workers in Food Preparation & Serving Related occupations.

Next, for each combination of the timescale of environment variation and control over the job choice in the calibrated model, I calculate implied lifetime standard deviations of cognitive skill requirements, and the average number of switches between jobs. Figure 3.12 shows the changes in the standard deviation of cognitive skill and the average number of job switches for different environmental signatures. Across all control levels, the number of job switches is decreasing as the timescale of environment variation is increasing. The largest variability of cognitive skill requirements is observed for workers in environments with the least control over their job choices and the shortest timescales of environment variation. For the highest values of control over the job choice, the standard deviation of cognitive skill requirements is higher than for some of the intermediate control environments. This is due to the fact that, in the higher control environment, workers with higher level of cognitive skill are able to choose occupations with higher cognitive skill requirements., i.e., the higher average standard deviation of cognitive skill requirements at higher control levels reflects the job choices of workers with larger stocks of cognitive skill.

Standard deviations of cognitive skill requirement and the number of jobs switches predicted for the 22 occupational categories are mapped into environments with different signatures using the standard deviations and the average job switch numbers implied by the estimated model. Figure 3.12 shows the results of this mapping superimposed on the cognitive investment response modes produced by the model. Each green marker on Figure 3.12 represents up to three occupational categories for which the given combination of timescale and control over the job choice produced the standard deviation of cognitive skill requirement and the average number of job switches closest to those predicted by the estimated regressions in Tables 3.7-3.8.

Occupational categories are distributed over a wide range of environmental signatures and across all three cognitive skill response mode regions. Workers in Legal, Education & Library, and Community & Social Services occupations have the most control over the job choice. Facing relatively infrequent and predictable changes in skill requirements, the workers in these occupational categories adapt to their occupational environments through developmental plasticity. Based on their initial skill endowment, such workers build up a stock of cognitive skill and choose jobs to maximize the benefit from the complementarity between their skill and the cognitive skill requirements in the jobs from these occupational categories.

Occupations in Construction & Extraction, Production, Food Preparation & Related Services, Transport & Material Moving, and Personal Care & Services are characterized by an intermediate level of control over the cognitive requirement and fall into the region of activational plasticity. Cognitive skill investment for the workers in these occupational categories is the least intensive. Changes in cognitive skill requirements are mostly accommodated through learning-by-doing, whereby the skill of the workers from these occupational categories evolves over time to meet the relatively small changes in skill requirements, without additional costly investment into skill.

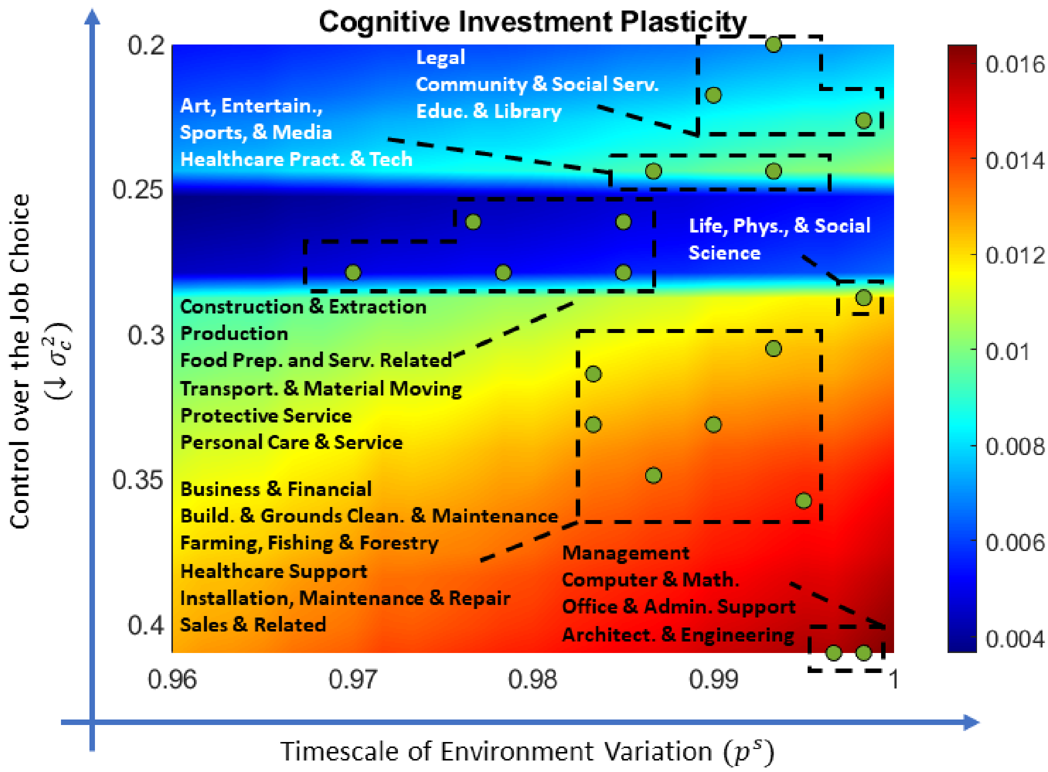

Figure 3.12: Occupational Environments and Adaptive Response Modes

Note: The figure shows the results of mapping 22 major occupational categories into the environment space produced by the calibrated model. For each combination of timescale and control over the job choice in the model, the average standard deviation of cognitive skill and the number of job switches were calculated over the lifetimes of a sample of 5,000 simulated workers with average initial skills (Figure 3.12). For each occupational category, the standard deviation of cognitive skill and the number of job switches were predicted for the worker with average initial skill using the estimated regressions in Tables 3.7-3.8. Predicted values are summarized in Table 3.A4. Occupational categories are mapped into the model environment space by finding the combination of timescale and control over the job choice that produces the standard deviation and the number of job switches closest to those predicted for a given occupational category. "Closest" means the minimal sum of square differences between standard deviations and number of switches produced by the model environment and the respective values obtained from predictions for a particular occupation.

As control over the cognitive skill requirement decreases, the average investment into cognitive skill starts to increase again. In the context of occupational environments, a rise in cognitive skill investment is largely driven by the workers from some of the most cognitive skill-intensive occupational categories. Workers in Business & Financial, Sales & Related, Installation, Maintenance & Repair, and, especially, Management, Computer & Mathematical, Architecture & Engineering occupations face significant variability of cognitive skill requirements over their lifetime. To be prepared for large increases in cognitive skill requirements, workers from these occupational categories equip themselves with large stocks of cognitive skill, i.e., adapt to changing labor market environment via bet-hedging.

Occupational categories with some of the lowest average cognitive skill intensities also fall into the region with the highest variability of cognitive skill requirements. Among these occupations are: Buildings & Grounds Cleaning & Maintenance, Farming, Fishing & Forestry, Healthcare Support, and Office & Administrative Support. Workers in these occupations may still invest some amounts into cognitive skill for bet-hedging purposes. However, this investment does not offset the effect of low average cognitive skill requirements leading to the depreciation of any preexisting skill stock. With very limited control over their job choice, and low average cognitive skill requirements, these workers end up with low stocks of cognitive skill, though they partially compensate for the losses in productivity by accumulating manual skill and/or choosing jobs with higher manual and interpersonal skill requirements.

Figure 3.13 compares the distributions of median cognitive skill requirements for workers who spent most of their lifetime in occupational categories that fall into the developmental and activational plasticity adaptive response mode regions, and for those who were mostly engaged in occupations that fall into the bet-hedging response mode region. For occupations associated with developmental and activational response modes, the largest fraction of workers is concentrated on the interval of median skill requirement between 0.2 and 0.4. In contrast, for occupations mapped into bet-hedging response mode, a large share of workers have either higher (above 0.4) or lower (below 0.2) median cognitive skill requirements. The share of workers with intermediate cognitive skill requirements in occupations from the bet-hedging region is much lower than in occupations from developmental and activational plasticity regions.

The coexistence of high and low median cognitive skill requirement workers at the lower levels of control over the job choice, together with a low share of intermediate cognitive skill requirement workers, corroborates the model-based result of bimodality in cognitive skill distribution in high skill variability environments. With the variability of cognitive skill requirement increasing, as control over the job choice decreases, the proportion of high and low cognitive skill ability workers rises, while the share of intermediate skill workers falls. This, in turn, find its reflection in the cognitive skill requirements of the jobs held by workers in the highly variable labor market environments[15].

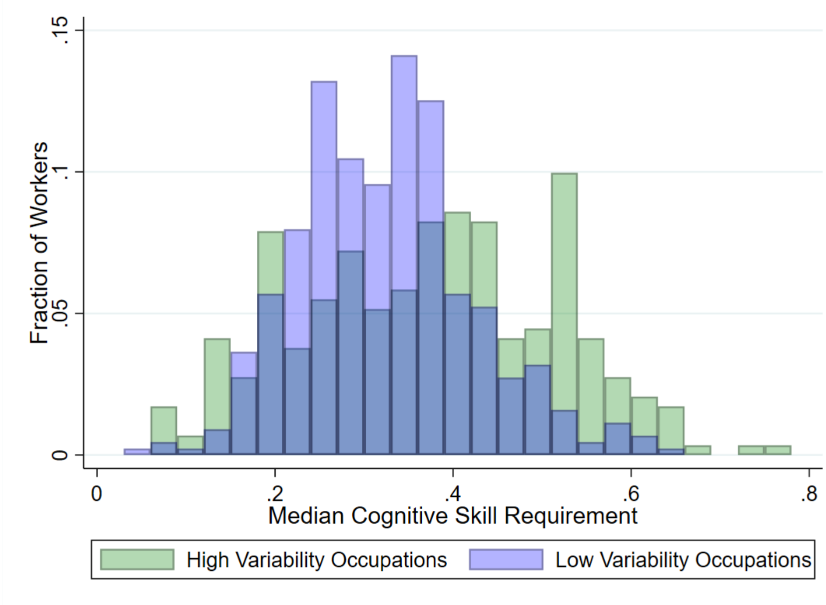

Figure 3.13: Skill Requirements in High and Low Cognitive Skill Variability Occupations

Note: The figure compares the distributions of median cognitive skill requirements over the lifetime of workers who spent most of their working years in high vs. low cognitive skill variability occupations. High cognitive skill variability occupations are the ones mapped into the bet-hedging response mode region, and low cognitive skill variability occupations are the ones mapped into developmental and activational plasticity response mode regions (see Figure 3.12).

3.5.3 Transitions Between Environments: Automation, AI, and Climate Change

In Section 3.4.2, I establish that most of changes in environmental signatures are not causing significant changes in the well-being of workers. However, transitions that require development of new adaptive responses are representing the tipping points. Workers undergoing such transitions experience significant changes in their lifetime consumption and unemployment risks. In this section, I interpret some major past and prospective labor market disruptions as transitions between adaptive response modes.

[15]While the bimodality at higher levels of cognitive skill variability in Section 3.4.4 is demonstrated using the estimated initial distribution of skills, the model specification used in this section, with all workers having the same average initial skill, can also produce a non-degenerate distribution of cognitive skill. The cognitive skill requirements in the jobs taken by workers at the beginning of their lifetime shape this distribution: cognitive skill depreciates rapidly in jobs with low cognitive skill requirements, while jobs with high cognitive skill requirements incentivize workers to invest into their skill due to high complementarity between cognitive skills and requirements.

A decrease in control over the cognitive skill requirements for workers in the activational plasticity region that leads to a transition to the bet-hedging region causes a significant rise in unemployment risk and a fall in lifetime consumption, relative to workers who were exposed to that lower control environment from the beginning of their lifetime (Figure 3.7 and Table 3.6). Automation, or routine-biased technological change (RBTC), as a technological development substituting for labor in tasks performed by moderately skilled workers (Acemoglu & Autor, 2011a), can represent this type a transition that leads to dramatic changes in employment and distribution of earnings. Practically, automation, together with offshoring, has led to the hollowing out of employment opportunities in middle-skilled occupations (Autor & Dorn, 2009a; Autor, 2010a). Workers previously performing routine cognitive (and routine manual) tasks were pushed to the lower control environments, where they could not choose with certainty the jobs that would be more closely aligned with their skill stocks.

The differential responses of workers to changes in the labor market environment due to automation, along with the automation/offshoring-induced changes in the demand side of the economy, resulted in a well-known phenomenon of labor market polarization (Autor et al., 2006b; Goos et al., 2009; Acemoglu & Autor, 2011a). In this context, a bimodality in cognitive skill distribution at the lower levels of control over the job choice, predicted by the model developed in this paper, suggests that the polarization can be, to a certain extent, a result of the adaptive responses of workers to the increased variability of the labor market environment resulting from the automaton/offshoring shock. In response to increased variability in cognitive skills, some of the workers (predominantly younger and relatively more skilled ones) managed to accumulate additional cognitive skill and joined high cognitive requirement occupations (Autor & Dorn, 2009a; Cortes, 2016a), while some of the workers ended up in the lowest cognitive skill occupations and unemployment (Cortes et al., 2017a; Jaimovich et al., 2021), resulting in depreciation of their preexisting stock of cognitive skill. The post-automation labor markets can therefore be represented as environments with less control over the job choice in terms of cognitive skill requirement, characterized by a bimodal distribution of cognitive skill that is observed as wage and employment polarization.

More recent technological developments, such as the introduction of AI, may have a two-sided effect on labor market environments. On the one hand, AI technology may potentially replace some higher cognitive skill jobs, such as teachers, media workers, and workers in legal occupations[16]. According to the mapping in Figure 3.12, the occupations to which these jobs belong fall into the region of developmental plasticity. The disappearance of these occupations would lead to reallocation of workers to occupations in environments with lower control over the job choice. Workers from the AI-replaced occupations may end up in either the activational plasticity or bet-hedging region. In the first case, although the workers may experience somewhat lower well-being compared to their initial environment, the higher stock of cognitive skill will allow them to perform better (in terms of higher lifetime consumption and lower unemployment risk) than workers who were in the activational plasticity region from the beginning of their lifetime (see Table 3.6 and Figure 3.7). Under the second scenario, the workers reallocating from developmental plasticity to the bet-hedging region may experience difficulties adapting. While their stock of cognitive skill is larger on average than that of the workers from the activational plasticity region, it may still not be enough for them to adapt to the highest cognitive skill variability environments.

On the other hand, AI may be used as an adaptive tool, facilitating the performance of certain cognitive tasks. AI-based tools can potentially close, either partially or fully, the gaps between worker's cognitive skills and job requirements[17]. From the perspective of workers, that would effectively increase their control over the job choice along the cognitive skill dimension. On the example of occupational categories, workers in Life, Physical, and Social science occupations (3.12), by outsourcing a part of their cognitive tasks to AI[18], can push themselves from bet-hedging to the activational plasticity region. Workers coming from more variable environments are likely to perform better than workers who experienced a more stable activational plasticity environment from the beginning of their lifetime (Table 3.6). However, in the long run, in case of further shocks to control over the cognitive skill requirements, subsequent generations of workers in Life, Physical and Social science occupations, starting their careers in activational plasticity region, may have difficulties adapting to environments associated with more intensive accumulation

[16] businessinsider.com/chatgpt-jobs-at-risk-replacement-artificial-intelligence-ai-labor-trends-2023-02 economist.com/graphic-detail/2023/04/14/chatgpt-could-replace-telemarketers-teachers-and-traders

[17] An example of this type of AI-based tools is GitHub Copilot. Trained on existing scripts written in various programming languages, it transforms verbal descriptions of a program into coding suggestions.

[18] For example, AI is already used for grant proposal writing , code generation, literature reviews, preparation of presentation materials, and for other cognitive skill-demanding and time-consuming tasks (https://www.nature.com/articles/d41586-023-03238-5 , https://www.nature.com/articles/d41586-023-03235-8).

of cognitive skill.

The previous two cases of changes in labor market environment were discussed from the perspective of changing control over the cognitive skill requirement. However, such natural sources of disruptions in labor market environment as climate change may represent movements along both control and the timescale axes. Climate change is associated with the movement of populations from affected regions to regions with more favorable climate conditions (McLeman & Smit, 2006; Feng et al., 2010; Missirian & Schlenker, 2017), with the increases in the average annual temperature above 25°C causing significant permanent migration responses (Bohra-Mishra et al., 2014). For migrating workers, destination regions may pose completely new labor market environments, with different levels of control over the job choice and the timescale of variation in skill requirements.

Under the impacts of climatic variations, the labor market environment of workers staying in the affected regions is also changing. The increases in the annual temperatures beyond certain thresholds have severe impacts on the productivity of agricultural sector (Schlenker & Roberts, 2009; Feng et al., 2010) and decrease the labor supply in occupations heavily exposed to outdoor temperatures (Graff Zivin & Neidell, 2014; Hsiang et al., 2017). Among the affected occupations are Farming, Fishing & Forestry, Construction & Extraction, and Production. While Farming, Fishing & Forestry belong to a highly variable environment (Figure 3.12), workers initially employed in Construction & Extraction and Production occupations may have to develop new adaptive responses and to suffer losses in their relative lifetime consumption and increased unemployment risks in the process of reallocating their labor supply to occupations affected by climate change to a lesser degree.

Additionally, increases in temperatures in the hottest seasons of the year decrease the output of the Wholesale & Retail Trade and Entertainment & Recreation Service industries (Hsiang, 2010). These industries, together with Mining and Construction, are among those with the highest average number of switches between jobs over the lifetime of workers (Figure 3.11), representing environments with frequent changes in skill requirements (i.e., the low timescale environments). As established in Section 3.4.3, transitions from lower to higher timescales of environment variation are associated with losses in relative lifetime consumption and higher unemployment risks due to the less intensive accumulation of cognitive skill at the lower timescales (Figure 3.8). Given this prediction of the model, workers from industries affected by a rise in the hottest season temperatures will experience difficulties adapting to the lower timescale environments represented by industries with more stable employment.

3.6 Conclusion

In this paper, I quantitatively evaluate the predictions of adaptation theory from modern biology and ecology in the context of changing labor market environments. To this end, I calibrate a model with multidimensional skills and job choices to the NLSY79 and O*NET data and simulate the workers' adaptive outcomes for different environmental signatures.

Large costs of mismatch and high skill-requirement complementarity, characterizing cognitive skill, result in the appearance of distinct adaptive response modes that are, in principle, similar to bet-hedging, acitvational and developmental plasticity — the response modes predicted in adaptive biology and ecology. At the same time, rapid accumulation and low costs of skill mismatch prevent the appearance of such response modes for manual skill, with the adaptive responses changing continuously across different labor market environments. Slow accumulation/depreciation and low costs of mismatch for interpersonal skill render it virtually fixed over a lifetime and across environments.

Transitions between the response modes of cognitive skill represent potential tipping points, whereby workers transitioning out of activational plasticity environments are experiencing the adverse effects on lifetime consumption and unemployment risks significantly above the average from transitioning between environmental signatures.

The highest levels of variability in cognitive skill requirement forge adaptive capacity, with workers transitioning from bet-hedging to activational plasticity regions performing better on average than workers native to an activational plasticity environment.

For high control environments, the cognitive skill distribution is concentrated between low and intermediate skill levels. With falling control over the cognitive skill requirement choice, the mass of intermediate cognitive skill workers begins to decrease, and the mass of workers with lower and higher cognitive skills increases. In other words, increased labor market environment variability leads to bimodality in the cognitive skill distribution.

I further discuss the sources of differences in environments faced by workers. Different environments can be represented by industries, occupational categories, labor markets for different educational groups, as well as by local labor markets, e.g., at the commuting zone level. Representing occupational categories as distinct labor market environments, I map them into adaptive response mode regions and discuss the adaptive capacity of workers from different occupations in face of automation, introduction of AI, and climate change. Finally, I relate the bimodality of cognitive skill distribution in the environments characterized by high variability of cognitive skill requirements with observed labor market polarization.

3.A Appendix

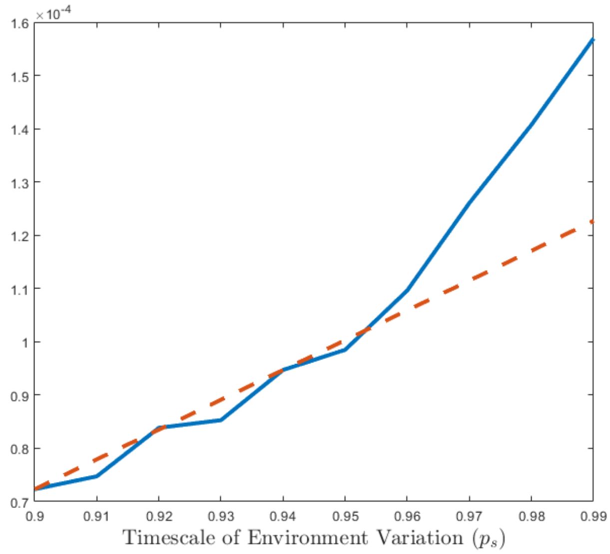

Figure 3.1: Average Cognitive Investment Plasticity across Timescales

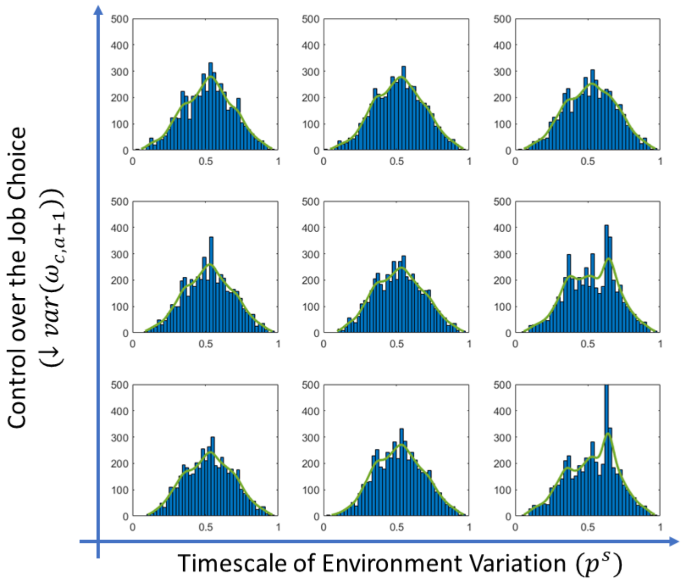

Figure 3.2: Distribution of Interpersonal Skill, 180th Month

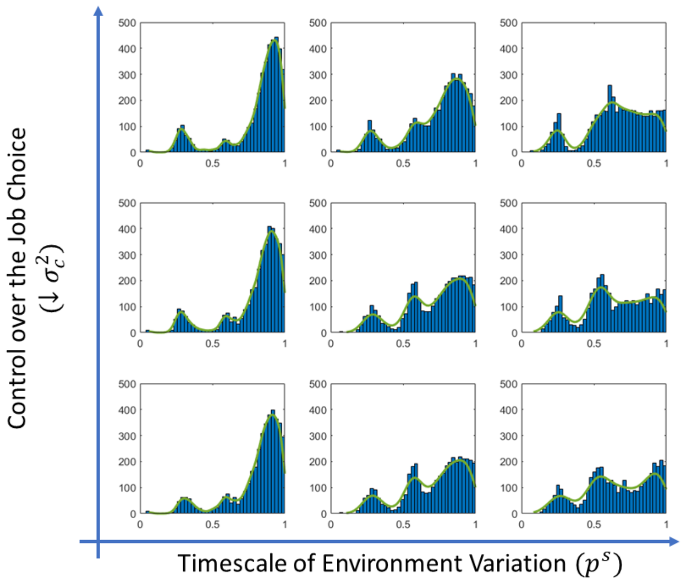

Figure 3.3: Distribution of Manual Skill, 180th Month

Note: For Figures 3.2-3.3, from top to bottom, distributions in rows are calculated for σ_c^2 equal to 0.25, 0.3, and 0.4. From left to right, distributions in columns are calculated for p^s equal to 0.9, 0.95, 0.99. The distributions are obtained from simulating the lifetime paths of 10,000 workers from the initial skill distribution estimated on the NLSY79 data. For all environments, control over the manual and interpersonal skill is fixed at their mean level. The green lines represent the kernel density estimates

Figure 3.4: Number of Job Switches Over the Lifetime by Major Occupational Categories

Note: Number of job switches over the lifetime is calculated using the weekly arrays of the NLSY79 data. Individuals are assigned to different categories based on the occupations in which they spent the largest number of months over their lifetimes.

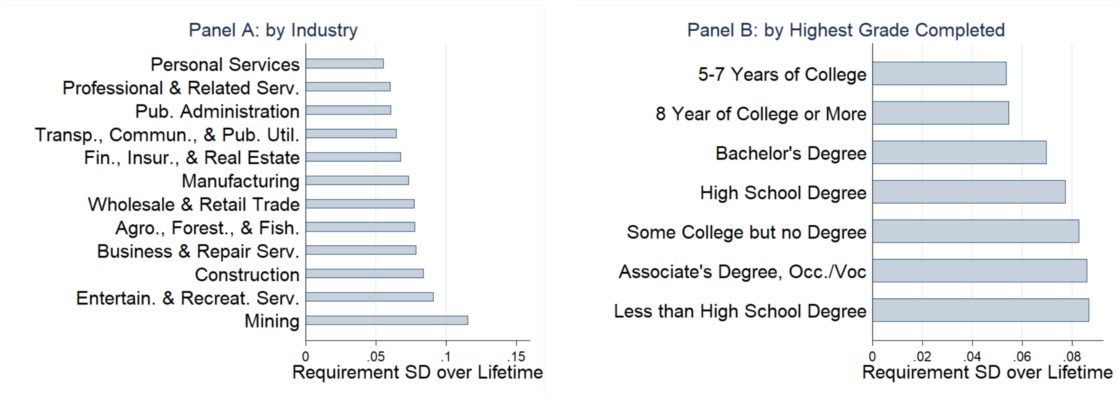

Figure 3.5: Standard Deviation of Cognitive Skill Over the Lifetime

Note: Standard deviations of the skill requirements are calculated over the lifetimes of individuals from the NLSY79 data, with changes in the skill requirements identified at the moments of job switching. For Panel A, individuals are assigned to different categories based on the industry in which they spent the largest number of months over their lifetimes. For Panel B, individuals are assigned to different categories based on the highest level of education they have achieved by the end of the observation period.

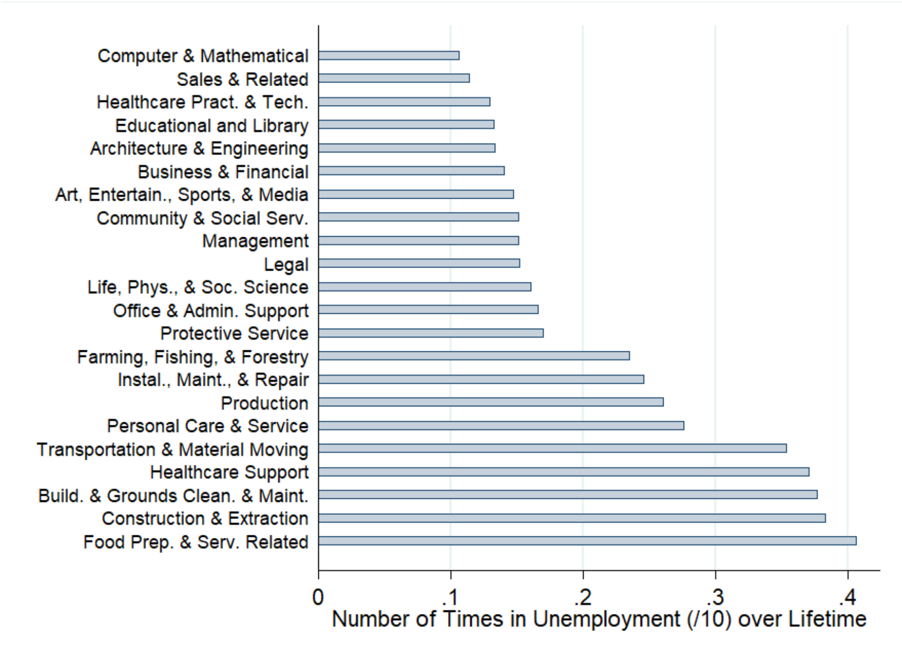

Figure 3.6: Number of Times in Unemployment by Major Occupational Categories

Note: The number of times falling into unemployment over the lifetime is calculated using the weekly arrays of the NLSY79 data. Individuals are assigned to different categories based on the occupations in which they spent the largest number of months over their lifetimes.

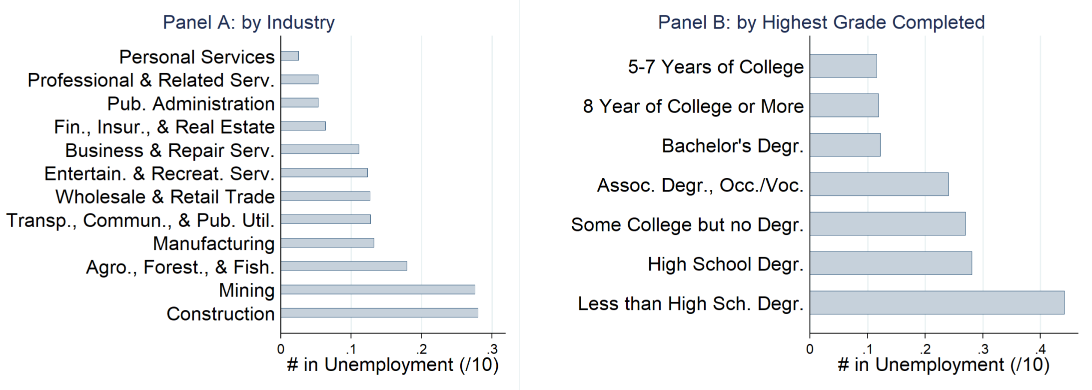

Figure 3.7: Number of Times in Unemployment Over the Lifetime

Note: The number of times falling into unemployment over the lifetime is calculated using the weekly arrays of the NLSY79 data. For Panel A, individuals are assigned to different categories based on the industry in which they spent the largest number of months over their lifetimes. For Panel B, individuals are assigned to different categories based on the highest level of education they have achieved by the end of the observation period.

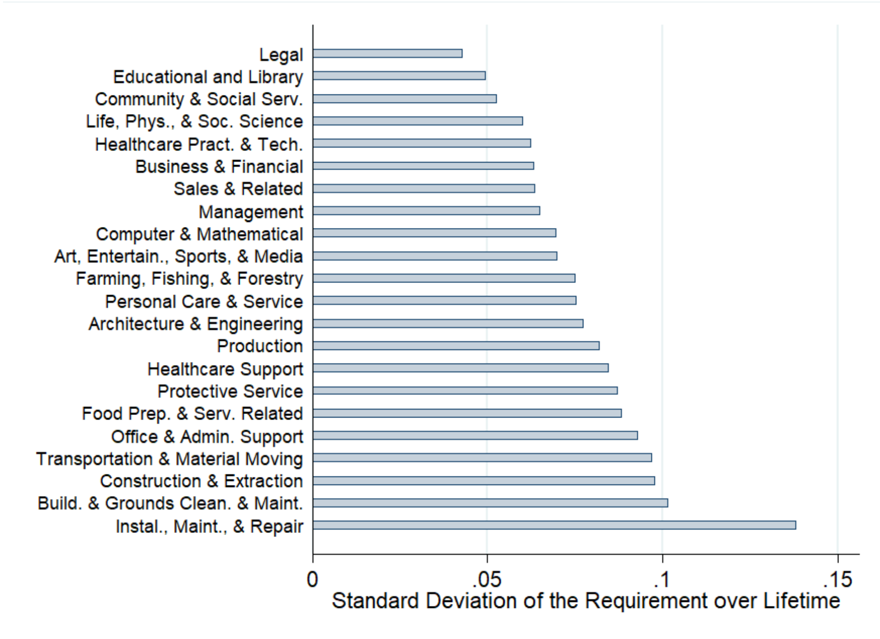

Figure 3.8: Standard Deviation of Manual Skill by Major Occupational Categories

Note: Standard deviations of the skill requirements are calculated over the lifetimes of individuals from the NLSY79 data, with the changes in the skill requirements identified at the moments of job switching. Individuals are assigned to different categories based on the occupations in which they spent the largest number of months over their lifetimes.

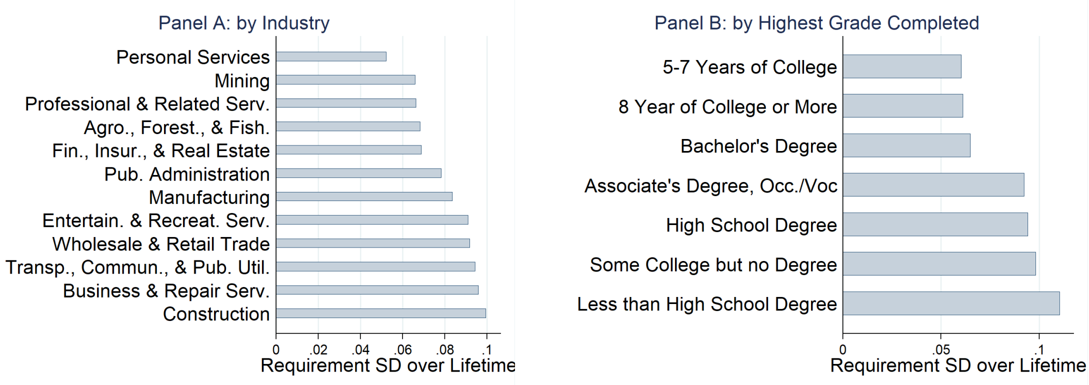

Figure 3.9: Standard Deviation of Manual Skill Over the Lifetime

Note: Standard deviations of the skill requirements are calculated over the lifetimes of individuals from the NLSY79 data, with changes in skill requirements identified at the moments of job switching. For Panel A, individuals are assigned to different categories based on the industry in which they spent the largest number of months over their lifetimes. For Panel B, individuals are assigned to different categories based on the highest level of education they have achieved by the end of the observation period.

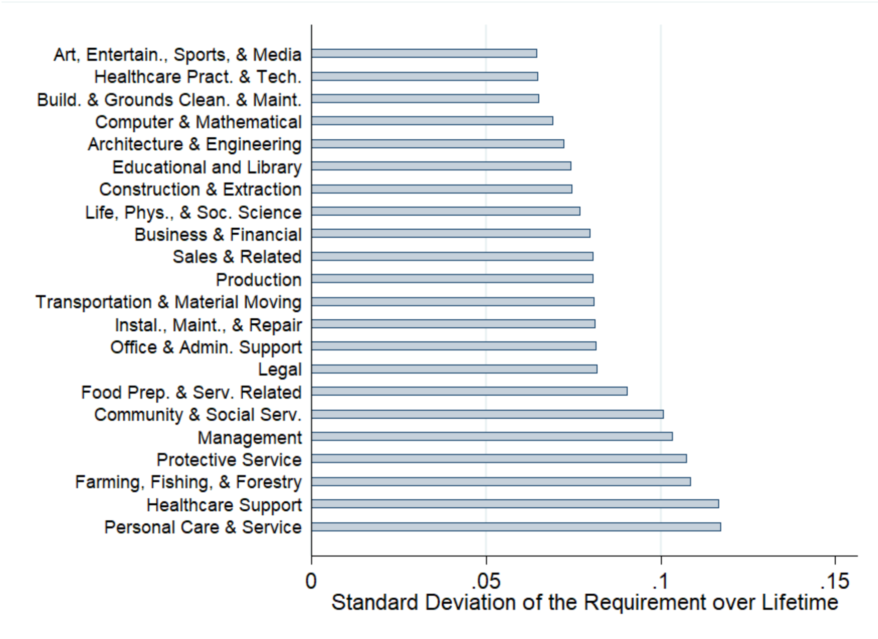

Figure 3.10: Standard Deviation of Interpersonal Skill by Major Occupational Categories

Note: Standard deviations of the skill requirements are calculated over the lifetimes of individuals from the NLSY79 data, with the changes in the skill requirements identified at the moments of job switching. Individuals are assigned to different categories based on the occupations in which they spent the largest number of months over their lifetimes.

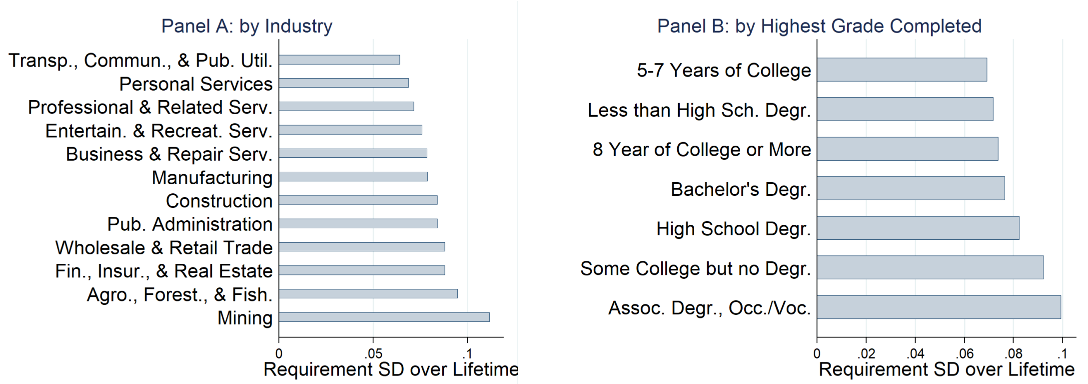

Figure 3.11: Standard Deviation of Interpersonal Skill Over the Lifetime

Note: Standard deviations of the skill requirements are calculated over the lifetimes of individuals from the NLSY79 data, with changes in the skill requirements identified at the moments of job switching. For Panel A, individuals are assigned to different categories based on the industry in which they spent the largest number of months over their lifetimes. For Panel B, individuals are assigned to different categories based on the highest level of education they have achieved by the end of the observation period.

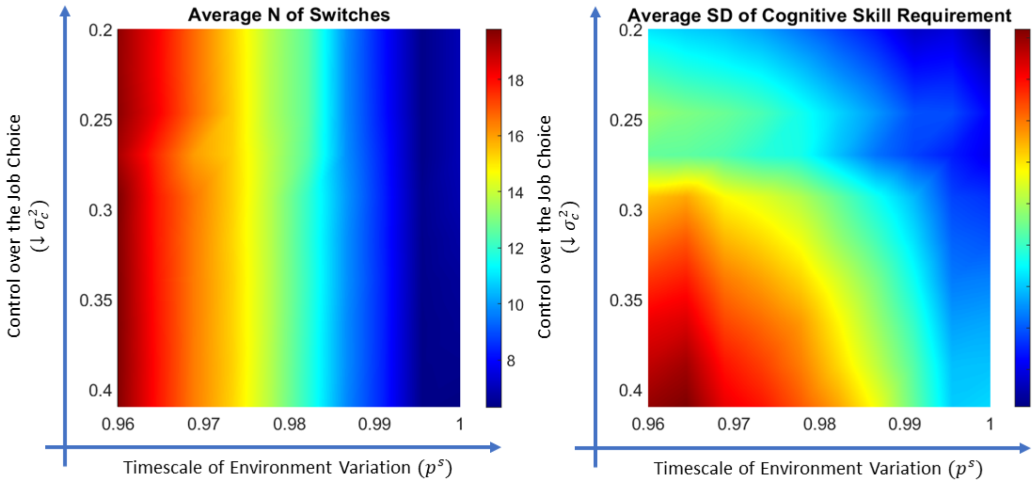

Figure 3.12: SD of Cognitive Skill and Number of Job Switches over Lifetime in the Model

Note: The figure shows the average number of job switches and the standard deviation of cognitive skill requirements associated with each combination of timescale and control over the job choice in the model (environmental signature). For each environmental signature, the average standard deviation of cognitive skill and the number of job switches were calculated over the lifetimes of a sample of 5,000 simulated workers with average initial skills.

Table 3.A1: Correlates of the Number of Times of Falling into Unemployment

	(1)	(2)	(3)	(4)
S_{C0}	-0.23*	-0.03	0.00	0.04
	(0.13)	(0.13)	(0.13)	(0.13)
S_{M0}	0.10	0.02	0.01	0.02
	(0.11)	(0.11)	(0.11)	(0.11)
S_{I0}	-0.12**	-0.08*	-0.09*	-0.08
	(0.05)	(0.05)	(0.05)	(0.05)
Years in labor union				0.001**
				(0.000)
Years with health limitations				0.002***
				(0.000)
Lives in SMSA, not central city				-0.04**
				(0.02)
US Citizen as of 1984				-0.09*
				(0.05)
Married most of lifetime				-0.07***
				(0.01)
Ever in jail				0.12***
				(0.04)
Constant	0.51***	0.29***	0.40***	0.53***
	(0.03)	(0.05)	(0.07)	(0.09)
Controls for max. eudcational degree	✓	✓	✓	✓
Controls for 1st and 2nd most frequent occupation		✓	✓	✓
Controls for 1st and 2nd most frequent industry			✓	✓
Observations	1326	1326	1326	1326
Adjusted R^2	0.12	0.20	0.23	0.27

Note: The table shows the results of the regression of the number of times of falling into unemployment over the lifetime for workers from NLSY79 data on a set of explanatory variables. Controls for educational degree, occupations, and industries include controls for all categories that are shown on Figures 3.10-3.11. Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.A2: Correlates of the Standard Deviation of Manual Skill Requirement

	(1)	(2)	(3)	(4)	(5)
S_{C0}	-0.14***	-0.10***	-0.05*	-0.07**	-0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
S_{M0}	0.10***	0.08***	0.04	0.04*	0.04*
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)
S_{I0}	-0.02	-0.01	0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years in labor union					-0.0002**
					(0.000)
Years with health limitations					0.0001
					(0.0001)
Lives in SMSA, central city					0.01
					(0.01)
US Citizen as of 1984					-0.00
					(0.01)
Constant	0.12***	0.09***	0.05***	0.03*	0.03
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Controls for max. eudcational degree	✓	✓	✓	✓	✓
Controls for # of job switches and average skill requirments		✓	✓	✓	✓
Controls for 1st and 2nd most frequent occupation			✓	✓	✓
Controls for 1st and 2nd most frequent industry				✓	✓
Observations	1210	1210	1210	1210	1210
Adjusted R^2	0.08	0.18	0.27	0.28	0.29

Note: The table shows the results of the regression of the standard deviation of manual skill over the lifetime of workers from NLSY79 data on a set of explanatory variables. Controls for educational degree, occupations, and industries include controls for all categories that are shown on Figures 3.10-3.11. Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.A3: Correlates of the Standard Deviation of Interpersonal Skill Requirements

	(1)	(2)	(3)	(4)	(5)
S_{C0}	0.04	0.09***	0.04	0.03	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
S_{M0}	-0.06**	-0.08***	-0.04	-0.04	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
S_{I0}	0.03**	0.04***	0.02*	0.02*	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Years in labor union					-0.0002***
					(0.000)
Years with health limitations					0.0002**
					(0.001)
Lives in SMSA, central city					0.01
					(0.01)
US Citizen as of 1984					-0.01
					(0.01)
Constant	0.07***	0.03***	0.12***	0.13***	0.14***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Controls for max. eudcational degree	✓	✓	✓	✓	✓
Controls for # of job switches and average skill requirments		✓	✓	✓	✓
Controls for 1st and 2nd most frequent occupation			✓	✓	✓
Controls for 1st and 2nd most frequent industry				✓	✓
Observations	1210	1210	1210	1210	1210
Adjusted R^2	0.02	0.11	0.20	0.20	0.21

Note: The table shows the results of the regression of the standard deviation of interpersonal skill over the lifetime of workers from NLSY79 data on a set of explanatory variables. Controls for educational degree, occupations, and industries include controls for all categories that are shown on Figures 3.10-3.11. Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.A4: Predicted Standard Deviations of Cognitive Skill and Number of Job Switches

Occupational Category	Predicted Standard Deviation of Cognitive Skill Requirement	Predicted Number of Job Switches
Architecture & Engineering	0.1330	0.7932
Healthcare Support	0.1211	1.1462
Build. & Grounds Clean. & Maint.	0.1188	1.1589
Personal Care & Service	0.1176	1.6198
Instal., Maint., & Repair	0.1170	1.0493
Food Prep. & Serv. Related	0.1151	1.5972
Management	0.1149	0.8864
Office & Admin. Support	0.1114	0.7731
Transportation & Material Moving	0.1099	1.3523
Farming, Fishing, & Forestry	0.1090	0.9306
Computer & Mathematical	0.1087	0.7820
Construction & Extraction	0.1035	1.3915
Protective Service	0.0997	1.0863
Production	0.0964	1.0904
Art, Entertain., Sports, & Media	0.0955	1.0422
Sales & Related	0.0951	0.7276
Business & Financial	0.0949	0.8585
Healthcare Pract. & Tech.	0.0908	0.8553
Life, Phys., & Soc. Science	0.0872	0.7853
Community & Social Serv.	0.0860	0.9019
Legal	0.0815	0.7773
Educational and Library	0.0807	0.8633

Note: The table shows predictions for the standard deviations of cognitive skill and the number of job switches across 22 occupational categories, calculated based on the estimated regressions reported in Tables 3.7-3.8. Predictions are calculated for workers with average initial skills (from the estimated initial skill distribution), holding a bachelor's degree, living in an SMSA central city, married, and with the US citizenship. The averages for each occupational category are used for the number of years in a labor union, years with health limitations, average cognitive, manual, and interpersonal skill requirements. The predicted number of switches for each occupational category is used in predictions of the standard deviations of cognitive skill.

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