Essays about Retraining and Human Capital

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This dissertation consists of three essays about retraining and human capital. In the first essay, I study the equilibrium effects of retraining in an economy with directed job search. Not only does retraining improve participants' skills, it also changes non-participants' optimal job search strategies and, in turn, their re-employment outcomes. I find that retraining reduces between-skill inequality, whereas it increases within-skill inequality. Eliminating retraining causes welfare losses equivalent to a 1.5 percent drop in consumption. Evaluating various labor market policies aimed to encourage retraining participation, I show that combining retraining with a more generous unemployment insurance benefit is the most cost-effective and welfare-maximizing policy.

The second essay explores the gender gap in retraining participation. I address four possible explanations on what causes women to participate in retraining more actively than men. Using the National Longitudinal Survey of Youth (NLSY97), I discuss the role of social skills, occupations, marital status, and non-college job opportunities. I find that the return to retraining increases with participants' social skills, which supports the hypothesis that retraining rates are higher for women because they benefit more from retraining thanks to their high social skills. I also raise the possibility that female-dominant professions are more supportive in terms of workers' education. Neither marital status nor non-college opportunities appear to explain the gender gap in retraining.

In the third essay, I investigate the effects of academic collaboration on research productivity. The human capital of a group of researchers is combined by the CES production technology and produces a research outcome measured by the quality of the paper. The estimated elasticity of substitution suggests that researchers are imperfect complements. I use the estimates to simulate the growth of human capital of a researcher under different collaboration scenarios. I find that collaborating with an equally productive coauthor generates a considerable

increase in human capital. The effects of collaboration persist over time. I show that the link between human capital and collaboration opportunities play an important role in explaining this persistence.

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Preface

I'm extremely grateful to my advisor Stefania Albanesi for her continuous support during my doctoral studies. I could not have imagined having a better advisor. I would also like to thank the rest of my thesis committee Daniele Coen-Pirani, Douglas Hanley, and Shu Lin Wee for their insightful comments, encouragement, and sometimes hard questions, all of which were essential to improve my research. Finally, I'm deeply indebted to my family and Daegun Lee for their love and support.

1.0 Skill-Biased Technological Change, Inequality, and the Role of Retraining

1.1 Introduction

It has been well documented that the share of employment in middle-wage routine occupations has declined in the U.S. labor market in large part due to automation and so-called Skill-Biased Technological Change (David et al., 2006; Acemoglu and Autor, 2011; David and Dorn, 2013). This trend has worsened re-employment prospects for the unemployed who previously held such occupations. They are more likely to fall into long-term unemployment, leave the labor force, or shift into low-wage service occupations (Lee and Wolpin, 2010; Cortes et al., 2014, 2017). Retraining could help unemployed workers to obtain jobs in growing occupations and sectors that usually require greater cognitive skills. Despite its potential role, retraining hasn't received as much attention as other policy responses to unemployment, such as unemployment insurance benefit or search assistance. To fill this gap, in this paper I study retraining in an economy with directed job search and use it to investigate the equilibrium effects of retraining on wage and employment.

I first document a set of novel stylized facts about retraining. Using the National Longitudinal Survey of Youth for both 1979 and 1997, I show how prevalent retraining is among unemployed workers, what affects unemployed workers' decisions to retrain, and whether it improves their career prospects. I find that (a) retraining rates among unemployed workers aged 23-34 in the NLSY79 are only around 2 percent, but the rates increase by about 5 percentage points in the NLSY97; (b) sex, race, marital status, learning ability, and asset holdings affect unemployed workers' participation in retraining; (c) the completion rate of retraining is low; and (d) conditional on completing retraining, retraining participants are more likely to get better-paying jobs that involve less routine, manual tasks and more non-routine, cognitive tasks.

Based on this evidence, I build a model with directed job search and retraining. I consider an economy comprised of two occupation groups (cognitive and routine), two types of workers (high- and low-skill) who are heterogeneous in several dimensions, and frictional labor markets. The model has two important features. First, low-skill unemployed workers are given a chance to upgrade their skills by participating in retraining. Retraining corresponds to college attendance since most training for unemployed workers in the U.S. takes this form (Jacobson et al., 2005a). Retraining entails an opportunity cost as well as monetary costs since participants need to forgo labor market activities while retraining. The completion of retraining is assumed to be stochastic, reflecting high college dropout rates among non-conventional students. Successful completion of retraining ensures workers higher wages and a higher probability that they leave the routine occupation for the non-routine cognitive occupation. As observed in the data, unemployed workers' age and wealth are primary determinants of retraining participation. Second, the labor market features directed search. As in Menzio and Shi (2010), Menzio et al. (2016), Eeckhout and Sepahsalari (2014), and Herkenhoff et al. (2016), unemployed workers decide which job to apply for. The labor market consists of multiple submarkets distinguished by workers' age, skill, and occupation. In each submarket, there is a continuum of firms that offer various wages. In equilibrium, there is an inverse relationship between wages and job finding rates. High-paying jobs are more difficult to obtain. Unemployed workers choose which job to apply for by comparing wages against the probability of employment. Workers' wealth is a crucial factor in their optimal search strategies. Workers with high asset levels choose to wait until they are matched with a high-paying job because they can endure prolonged unemployment by relying on their savings. On the contrary, low-asset workers choose to apply for low-paying jobs so that they can get out of unemployment as quickly as possible.

Retraining affects the wage distribution through workers' job search strategies, asset holdings, and the income tax rate. The opportunity to retrain increases the value of unemployment by expanding unemployed workers' choice sets. Higher value of unemployment induces workers to make bolder choices when they apply for jobs. They choose to apply for higher-paying jobs at a given asset level. Consequently, wages increase for low-skill workers. Meanwhile, retraining decreases participants' asset holdings. Due to the monetary and opportunity costs of retraining, the participants are likely to hold low levels of assets. That makes them apply for low-paying jobs, offsetting some of the positive effects of retraining on wages. Moreover, as more workers end up at the lower end of the wage distribution, the variance of wages increase. Lastly, retraining increases after-tax wages by reducing the income tax rate. The equilibrium income tax rate is determined as the ratio of the government spending on unemployment insurance benefit to the income tax revenue. As more high-skill workers are created through retraining, the income tax revenue increases, and therefore, the income tax rate decreases.

The model is calibrated to the U.S. economy to the NLSY79. The calibrated model matches the mean retraining rate by age well. The model also does a good job of generating the rise in retraining between the NLSY79 and NLSY97 cohorts. To see this, I adjust a set of parameters that capture the changes in the labor market that the NLSY97 cohort experienced such as the increase in wage premium, the decrease in job finding rates, and the increase in job separation rates. The model explains around 79 percent of the increase in retraining participation observed in the data. The changes in job transition rates for low-skill workers play a bigger role than the changes in wage premium do, implying that grim prospects in the labor market for low-skill workers are the most important motive to retrain.

Using the model, I make three quantitative contributions. First, I study the effects of retraining on wage inequality. Since the collapse of middle-wage jobs is considered a primary source of rising inequality, it is important to understand how retraining affects it. To this end, I compare the benchmark economy with retraining to a counterfactual economy where retraining is not possible. I find that in the economy where unemployed workers have a retraining option, low-skill workers go for higher-paying jobs and as a result, earn higher wages. This decreases the wage gap between low- and high-skill workers. However, within-skill inequality measured by wage variance is larger in the benchmark economy for both low- and high-skill workers. Newly-created high-skill workers tend to have low asset levels since they ran down their savings while retraining. To avoid extended unemployment, they apply for low-paying jobs, making the wage distribution more dispersed. Similarly, the variance of wages among low-skill workers is higher in the benchmark economy since the participants who fail to complete retraining end up with low-paying jobs.

Second, I investigate the welfare effects of retraining. I assume that the workers in the benchmark economy are transferred to an economy without retraining and calculate the welfare changes. Moving to the economy without retraining makes everyone worse-off. It causes a 1.5% drop in the average welfare. For high-skill workers, welfare losses come from exclusively from the income tax increase. For low-skill workers, the income tax increase explains 38% of the total losses. The losses also come from changes in optimal job search strategies and savings. With a lack of retraining, low-skill workers take safe job search strategies. Facing a low probability of unemployment, they are in less need of precautionary savings. It alleviates some of the total losses. The lost opportunities of upgrade skill accounts for the remaining welfare losses for low-skill workers.

Lastly, I suggest several government policies that can encourage retraining participation and evaluate the effectiveness of each policy by comparing their effects on retraining rates and required tax increases. Universal free retraining results in the highest retraining participation. However, it comes with a high tax increase. I find that guaranteeing higher unemployment insurance benefit for retraining participants achieves the biggest increase in retraining rates for a given tax increase. It is the policy that maximizes the average welfare as well.

This paper is related to several strands of literature. First, a number of studies such as Meyer (1995), Heckman et al. (1999), Jacobson et al. (2005a), Jacobson et al. (2011), Nie (2010), and Barr and Turner (2015) investigate the determinants and consequences of job-training and education programs for unemployed workers. These studies tend to conduct individual-level analysis focusing on the effects of retraining on individual re-employment outcomes. Nie (2010) is the only exception. He develops a structural framework of retraining and uses it to examine macroeconomic effects of retraining. Specifically, he shows how reforms of retraining programs in Germany affect aggregate employment, unemployment, and output. This paper is different from Nie (2010) in that, by incorporating directed search in the model, it takes account of the effect retraining has on non-participants as well, which allows for a more general welfare and policy analysis.

From the model perspective, this study is indebted to a growing literature of directed job search models such as Menzio and Shi (2010, 2011), Menzio et al. (2016), Eeckhout and Sepahsalari (2014), and Herkenhoff et al. (2016). I contribute to this literature by applying the theory of directed job search to an important social issue of retraining low-skill workers. The directed job search framework has been used in examining the effects of passive labor market policies such as unemployment insurance benefits (Acemoglu and Shimer, 1999; Chaumont and Shi, 2017). To my knowledge, this is the first attempt to use this framework to analyze active labor market policies such as retraining. Lastly, it is also related to an extensive literature on skill-biased technological change and job polarization. This paper extends this literature by assessing the potential role of retraining in mitigating the negative consequences of the decline in middle-wage occupations.

This paper is structured as follows: Section 2 describes the data and empirical results. Section 3 presents the model. Section 4 discusses the calibration strategy and the quantitative analysis, and Section 5 provides the conclusion.

1.2 Empirical Evidence

In this section, I present a number of new stylized facts about retraining that will motivate the setup of my model. Mainly, I look at (a) how prevalent retraining is in the U.S. (b) what characteristics retraining participants have and, (c) how retraining changes participants' re-employment wages and occupations later.

1.2.1 Data and Sample Selection

My empirical results are based on both the NLSY79 and NLSY97. The NLSY79 and NLSY97 are longitudinal studies that follow American youth born between 1957-1964 and between 1980-1984, respectively. Using both NLSY surveys together provides two advantages. First, since the NLSY97 only has information on relatively young population, also using the NLSY79 allows me to observe retraining patterns for older population. Second, since the NLSY79 survey was made before the decline in the routine occupation had started whereas the NLSY97 survey was made when it had been ongoing for a while, comparing the two surveys' population provides some insight into how the decline of routine occupation has impacted retraining participation. Unlike the NLSY79, the NLSY97 doesn't include the economically disadvantaged non-black, non-Hispanic oversample and the military sample. To make the population being studied comparable across two surveys, I exclude these extra samples from the NLSY79.

I first restrict the sample to those who ever experienced at least one Employment Unemployment Employment transition. To focus on the impact retraining has on low-skill workers, I exclude those who had a college degree at the beginning of the unemployment spell. I then define retraining participants as those who enrolled in a 2- or 4-year college during the unemployment spell. The panel structure of the NLSY allows me to find the exact time that a person lost his job and the time that he started college. A person is considered to have participated in retraining if he enrolled in a 2- or 4-year college after he had lost his job and before he had found a new one. The way I define retraining participants is in line with the fact that much of retraining programs for unemployed workers in the U.S. takes place in the form of regular college courses (Jacobson et al., 2005a).[1] Besides, looking at college programs rather than particular job training programs is most suited for the purpose of the study since most highly demanded jobs require a college degree.

One concern about the way I define retraining participants is that with the information available in the NLSY surveys, it is difficult to perfectly distinguish retraining participants from those who are simply putting off going to college. However, this problem doesn't seem critical. The youngest group in the sample is 23 years old, the age at which most people finish college education. Plus, the workers in the sample have the average of about 5 years of full-time working experience prior to unemployment. So, it's reasonable to assume that they are different than those who take one or two gap years for some experience before starting college.

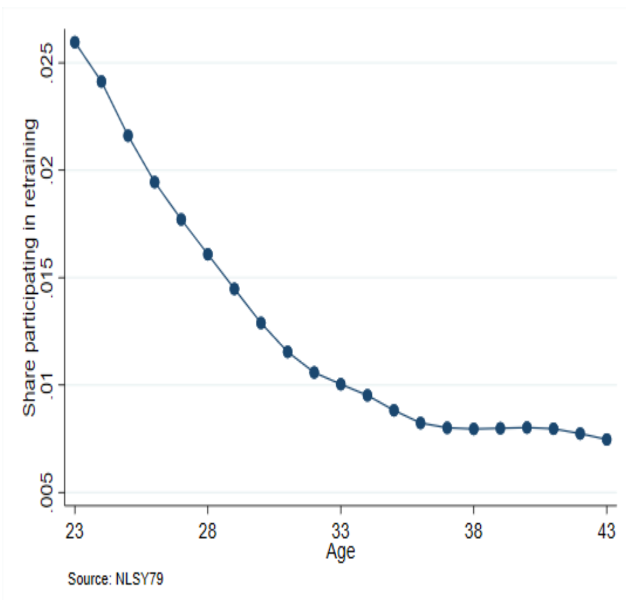
The data is at the unemployment spell level. There are a total of 11,981 spells for a total of 4,347 individuals in the NLSY79, and a total of 5,050 spells for 2,610 individuals in the

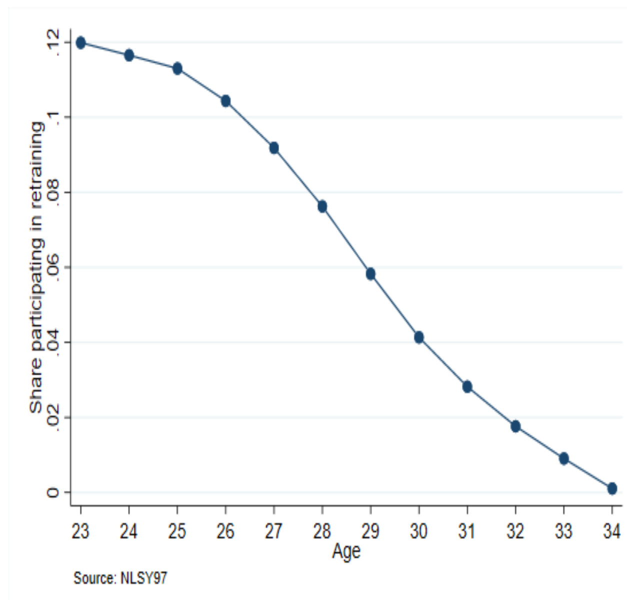
[1]Public-sponsored retraining in the U.S. for unemployed workers is provided through the Workforce Investment Act. Unemployed workers can receive three tiers of services: core services (e.g. job search assistance), intensive services (e.g. comprehensive assessment, case management), and training (e.g. classroom training, on-the-job training). Workers who reach the training level of services are given a voucher referred to as Individual Training Accounts, which they can use to obtain retraining from certified providers, most of which are 2-year public colleges. (Eberts, 2010; Frank and Minoff, 2005)

NLSY97.

1.2.2 Incidence of Retraining

Figure 1 plots the fraction of retraining participants among the unemployed by age. The top panel plots the results from the NLSY79, and the bottom panel from the NLSY97. Retraining rates decrease along age, which is not surprising since older workers have fewer working years left to enjoy the rewards of retraining. The figure also shows that there has been a big increase in retraining for the younger cohorts. At the age of 23, only 2.2% of unemployed workers retrained in the NLSY79. The number increases to 10.8% among the NLSY97 cohorts.[2] I discuss the sources of this increase in the later part of the paper.





Note: This figure presents the share of retraining participants among the unemployed at each age. The left figure is from the NLSY79 and the right figure the NLSY97.

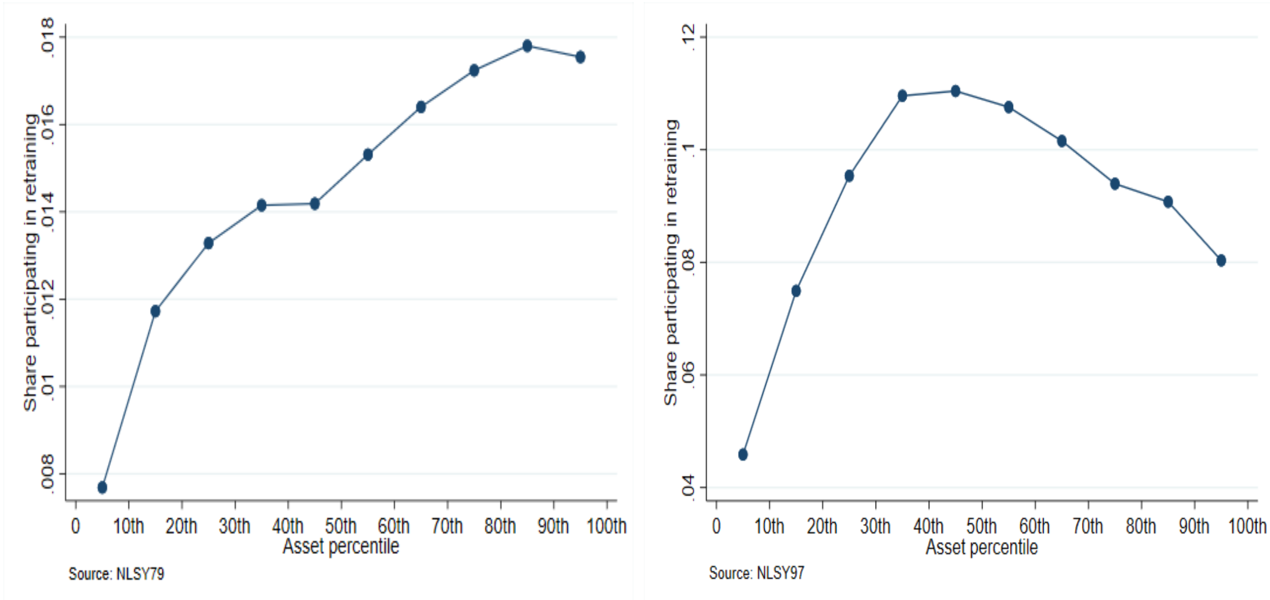
Figure 1: Retraining rates by age

[2] To my knowledge, Barr and Turner (2015) is the only recent study on prevalence of retraining. Using the CPS, they found 13 % of unemployed individuals aged 20-30 were enrolled in college between 2008 and 2011, and from the SIPP, they found between 15 and 20% of UI recipients aged 20-30 enrolled within 6 months of initial UI receipt over a similar period. Their numbers are bigger than what I found possibly because the definition of retraining participants I used is more restrictive.

1.2.3 Characteristics of Retraining Participants

Table 1 compares basic summary statistics between retraining participants and non participants. Retraining participants are slightly younger, more likely to be female, more likely to be black, less likely to be Hispanic, and less likely to be married. These findings are consistent with what Barr and Turner (2015) found from the CPS. Retraining participants also have a higher cognitive ability measured by Armed Forces Qualifications Test score (AFQT).

I found no significant differences between the two groups in the net value of total assets they hold and hourly wages they used to earn pre-unemployment. Since there are more young people, females, and minorities among retraining participants, I compared asset holdings and previous wages adjusted for the effects of age, sex, race, marital status, and AFQT scores. The results show that retraining participants have higher residual assets. The difference is significant at the 10% significance level. Figure 2 gives a closer look on the relation between asset holdings and retraining. The figure plots retraining rates over the distribution of residual total assets. The fraction of retraining participants among the unemployed increases as assets percentile increases. In the high end of the asset distribution, however, the fraction flattens then slightly decreases.



Note: This figure plots retraining rates over the residual asset distribution. The left figure is from the NLSY79 and the right figure the NLSY97.

Figure 2: Retraining rates by asset percentile

Unemployed workers' previous occupations can affect their retraining participation as well. Those who previously worked in the occupations where higher-education is rewarded more (e.g. non-routine cognitive occupation) may have a stronger incentive to retrain. On the other hand, those who worked in the occupations in decline (e.g. routine occupation) may want to retrain more so that they can move to the occupations in expansion. Following the literature (Acemoglu and Autor, 2011; David and Dorn, 2013; Cortes et al., 2014, 2017), I classify workers' previous occupations into four groups: non-routine cognitive, non-routine manual, routine cognitive, routine manual[3]. I then compare the share of each occupation group between retraining participants and non-participants. Since the share of women, who have a higher participation rate than men, varies across occupations, I do this analysis separately by

[3]The occupation is considered routine if the tasks can be done by following well-defined instructions. The occupation is considered non-routine if it involves tasks that require flexibility, creativity, problem-solving, or human interaction. Cognitive and manual occupations are distinguished by the relative extent of mental to physical activity. Non-routine cognitive occupations include Professional, Managerial and Technical Occupations. Routine cognitive occupations include Sales and Clerical Occupations. Routine manual occupations include Production, Craft and Repair Occupations, Operators, and Transportation and Material Moving Occupations. Non-routine manual occupations include Service Occupations.(Cortes et al., 2017)

	All		Non participants		Participants		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Age	26.41	2.72	26.51	2.77	25.44	2.04	***
Percent male	45.88	0.50	46.70	0.50	37.85	0.49	***
Percent black	28.99	0.45	28.64	0.45	32.47	0.47	**
Percent Hispanic	22.00	0.41	22.36	0.42	18.49	0.39	**
Percent married	25.43	0.44	25.80	0.44	21.72	0.41	*
Total real asset ($)	24509.21	37408.13	24473.15	36865.67	24864.89	42429.83	
Residual total asset($)	2.04E-05	36916.82	-274.25	36378.16	2704.17	41806.26	*
Real hourly wages($)	13.22	25.77	13.21	25.82	13.36	25.29	
Residual wages($)	-8.34E-09	26.35	-0.06	25.78	0.63	25.23	
Percent non-routine cognitive	25.52	0.44	25.43	0.44	26.45	0.44	
Percent non-routine manual	21.41	0.41	20.94	0.41	26.02	0.44	**
Percent routine cognitive	34.85	0.48	34.94	0.48	33.98	0.47	
Percent routine manual	18.22	0.39	18.69	0.39	13.55	0.34	***
AFQT	43679.24	26345.29	43096.80	26282.72	49142.68	26347.08	***
N of Obs	5,050		4,585		465		

Note: *Significant at 10%, **Significant at 5%, ***Significant at 1%
The corresponding table for the NLSY79 can be found in Table 26.
Source: NLSY97.

Table 1: Descriptive statistics (participants vs. non-participants)

sex. The results are reported in Table 2. For women, I find no significant differences in previous occupations between retraining participants and non-participants. For men, however, retraining participants have a higher fraction of former non-routine manual workers and a lower fraction of former routine-manual workers. This suggests that low retraining participation among men stems from low participation among former routine-manual workers, despite the fact that it is the occupation most vulnerable to automation and international trade and, therefore, its workers need retraining the most.

A. Male	Non-participants	Participants	
Percent non-routine cognitive	19.6	19.3	
Percent non-routine manual	21.0	29.5	***
Percent routine cognitive	27.0	26.7	
Percent routine manual	32.3	24.4	**
B. Female	**Non-participants**	**Participants**	
Percent non-routine cognitive	30.5	30.8	
Percent non-routine manual	20.9	23.9	
Percent routine cognitive	41.9	38.4	
Percent routine manual	6.8	6.9	

Note: *Significant at 10%, **Significant at 5%, ***Significant at 1%
The corresponding table for the NLSY79 can be found in Table 27.
Source: NLSY97.

Table 2: Occupation by sex (participants vs. non-participants)

1.2.4 Outcomes of Retraining

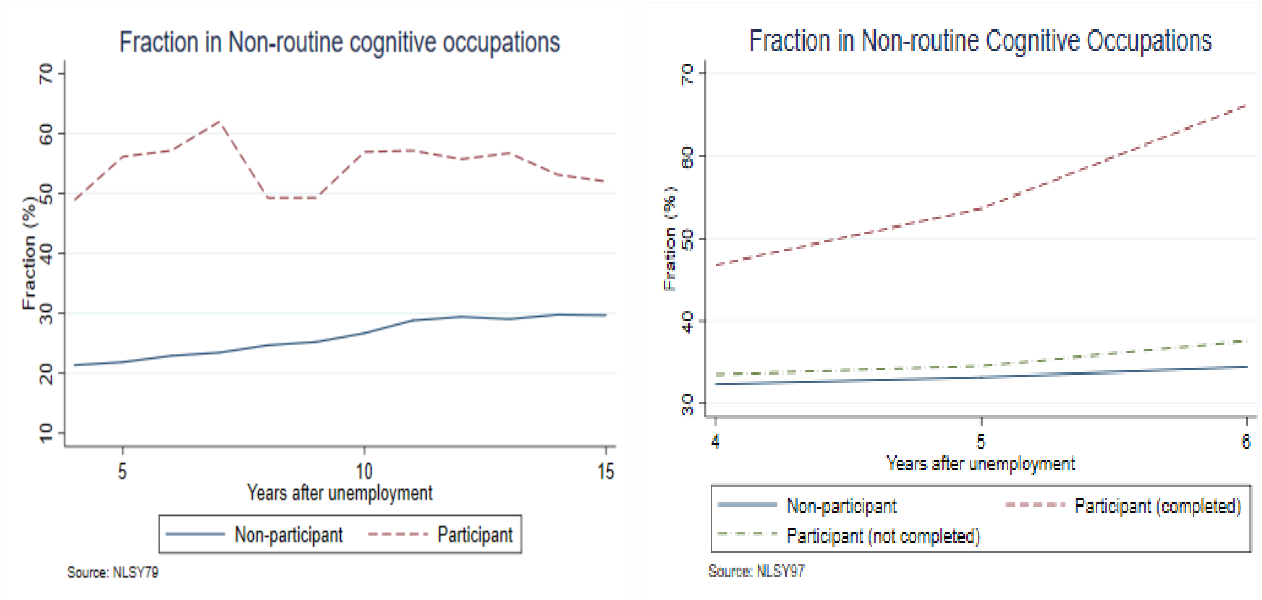
In this section, I examine the outcomes of participating in retraining. Before doing this, I first see how many retraining participants successfully complete retraining. I compute the fraction of retraining participants who earn either an Associate's degree or a Bachelor's degree by years from the beginning of the unemployment spell. The success rate of retraining is quite low. As shown in Table 3, after 4 years from the start of unemployment, only about 33 percent of retraining participants hold an Associate's or Bachelor's degree. After 6 years, the number increases to about 42 percent. Only just less than a half were able to get a college degree as a result of retraining. This finding is consistent with that non-traditional students who are usually older than traditional students have higher college dropout rates than others.

	Percent holding a college degree
t+4	32.92
t+5	38.14
t+6	42.24

Note: t is the time when a sample lost his job
Source: NLSY97.

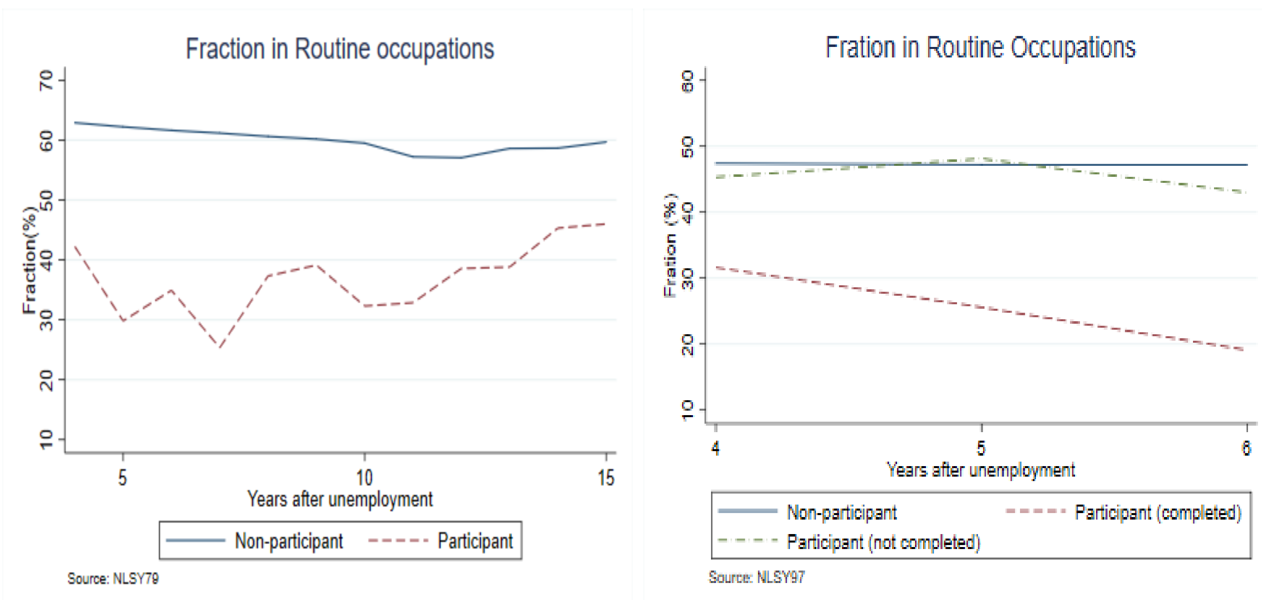
Table 3: Retraining completion rates

1.2.4.1 Occupation Switching Patterns I begin by comparing the occupation switching patterns among unemployed workers. I see if participating in retraining affects the probability of a worker moving to a higher-ranked job in the job ladder. Again, I use the occupation classification of Acemoglu and Autor (2011). Ranked by occupational mean wage, non-routine cognitive occupations are in the top, non-routine manual occupations are in the bottom, and routine occupations are in the middle. Figures 3-5 show the share of workers re-employed in each occupation group. The share of workers re-employed in the non-routine cognitive occupation, the highest ranked group, is higher for participants than non-participants. The share re-employed in the routine occupation, which has been in decline for the past couple of decades, is lower among the participants. The share in the non-routine manual occupation, the lowest ranked group, is also lower for participants. However, the results for retraining participants who fail to get a college degree aren't very different from those for non-participants.



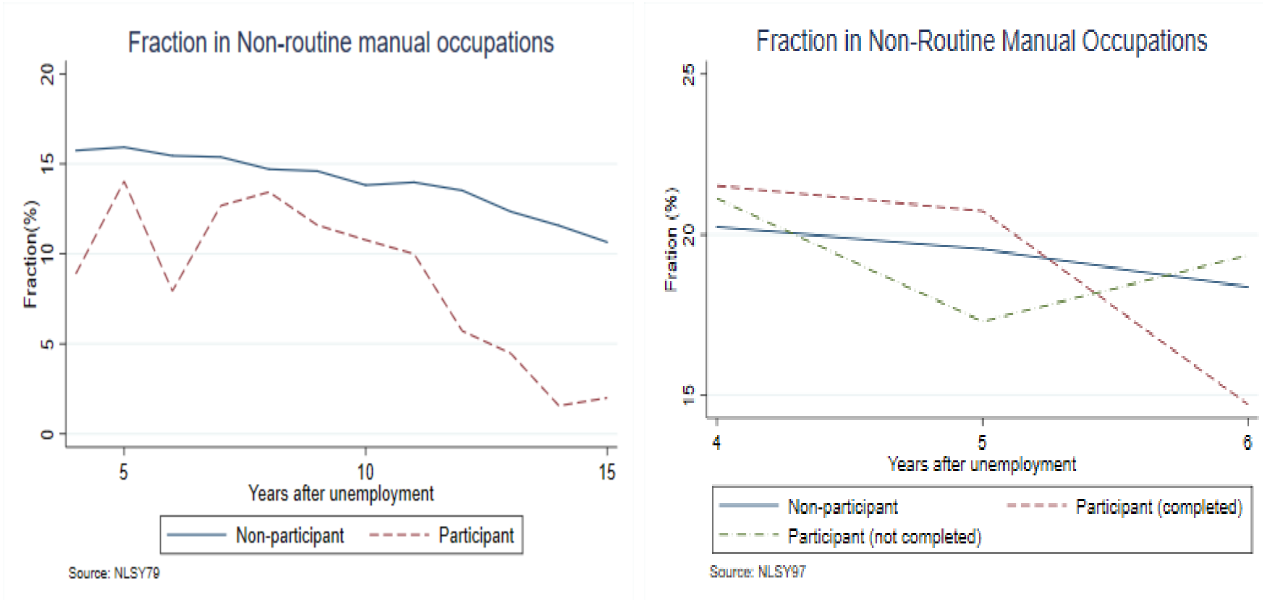
Note: This figure presents the share of workers who work in non-routine cognitive occupations. The horizontal axis shows years after the job loss.

Figure 3: Fraction in non-routine cognitive occupations



Note: This figure presents the share of workers who work in routine occupations. The horizontal axis shows years after the job loss.

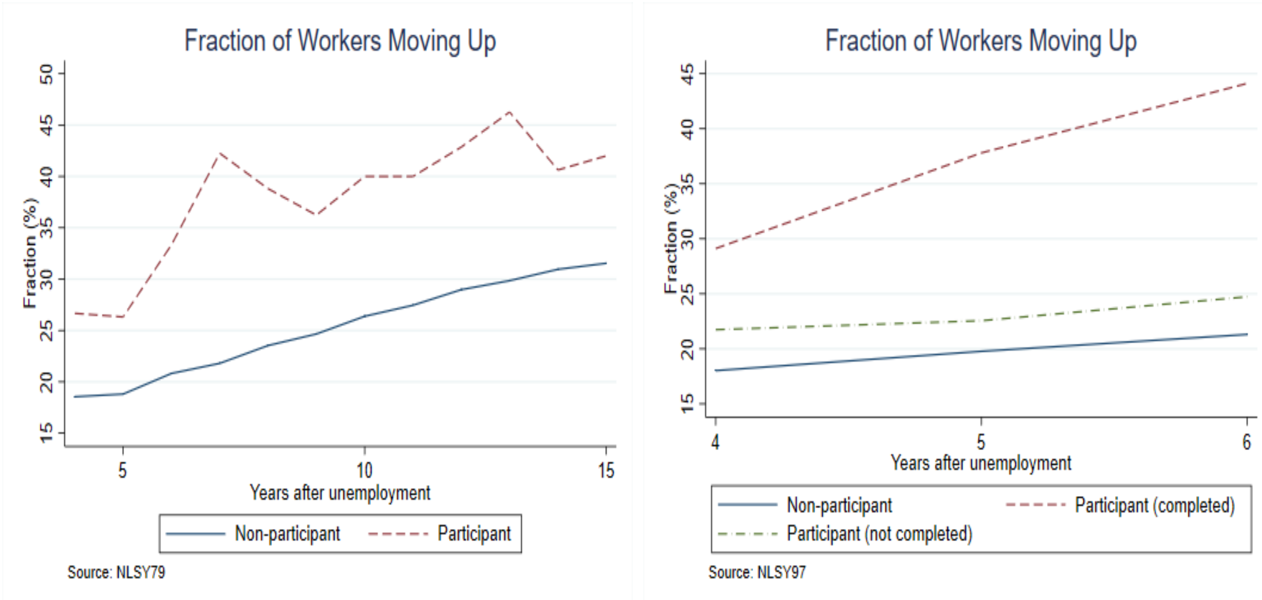
Figure 4: Fraction in routine occupations



Note: This figure presents the share of workers who work in non-routine manual occupations. The horizontal axis shows years after the job loss.

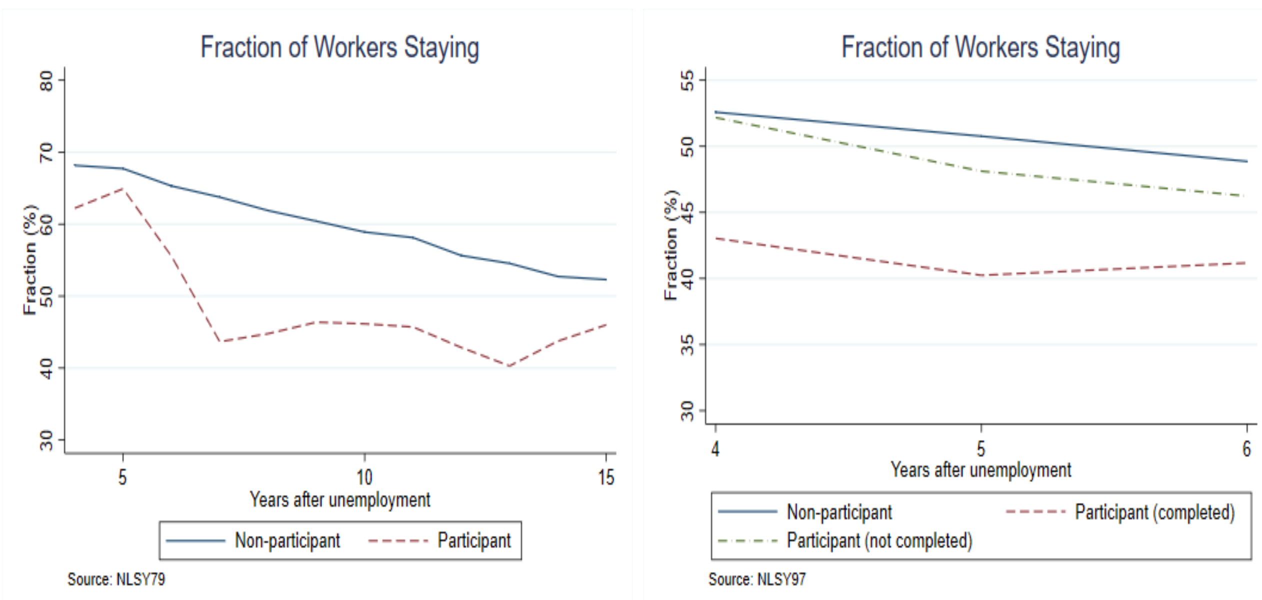
Figure 5: Fraction in non-routine manual workers

I also classify the sample according to the direction of the switches. The results are presented in Figures 6-8. The share of workers who switched to higher-ranked occupations (e.g. from routine to non-routine cognitive, from non-routine manual to routine/non-routine cognitive) is higher for participants. Both the share of stayers and the share of those who moved down the ladder (e.g from non-routine cognitive to routine/non-routine manual, from routine to non-routine manual) are lower among participants. In the NLSY97, the fraction moving down is actually higher for participants at the time they would have just finished retraining, but it decreases as time passes and becomes lower than non-participants eventually. Overall, retraining participants have a better chance of finding a better job when they are re-employed than non-participants. It is not the case, though, for those who stop retraining without a degree.



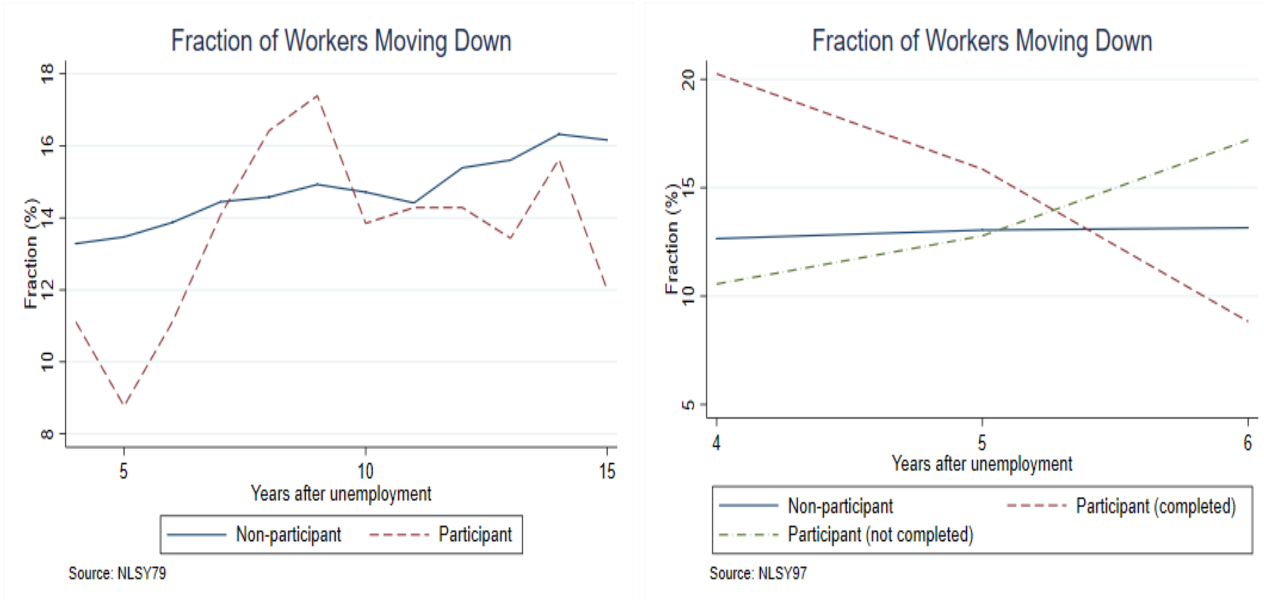
Note: This figure presents the share of workers who moved up the job ladder (e.g., workers who switched from routine occupations to non-routine cognitive occupations). The horizontal axis shows years after the job loss.

Figure 6: Fraction of workers who moved up the job ladder



Note: This figure presents the share of workers who went back to the occupation they had held prior to unemployment. The horizontal axis shows years after the job loss.

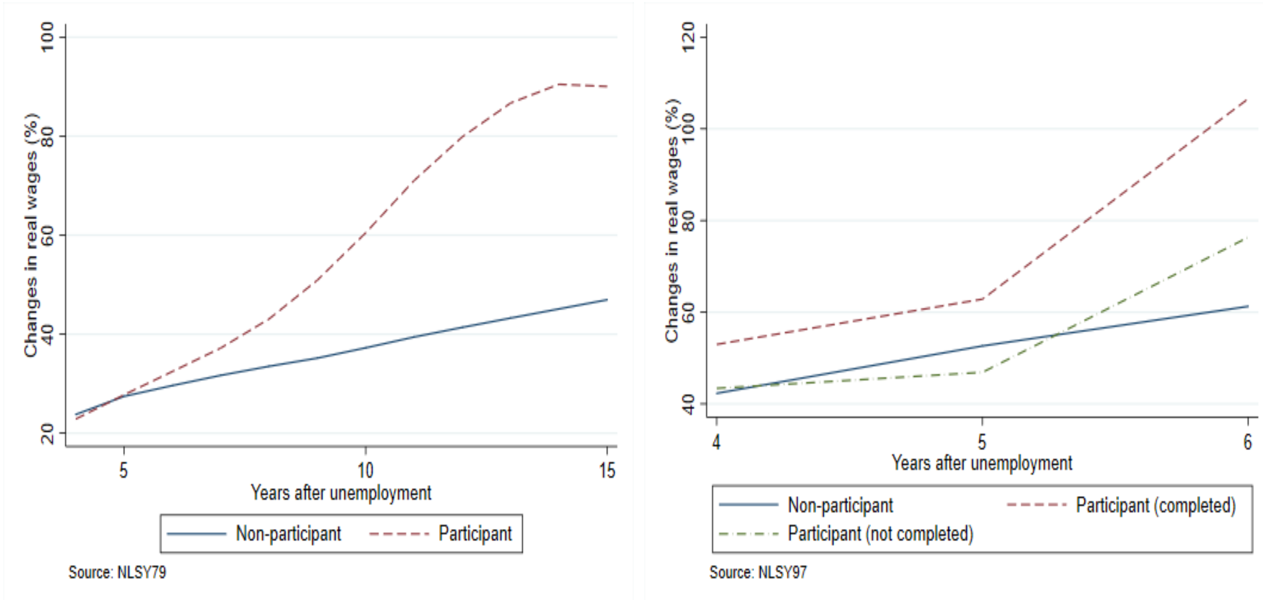
Figure 7: Fraction of workers who stayed in the same occupation group



Note: This figure presents the share of workers who moved down the job ladder (e.g., workers who switched from non-routine cognitive occupations to routine occupations). The horizontal axis shows years after the job loss.

Figure 8: Fraction of workers who moved down the job ladders

1.2.4.2 Wage Changes Now I turn my interest to the effects of retraining on wage changes. Figure 9 compares wage changes between participants and non-participants. After 4 years from the beginning of unemployment, wages of retraining participants are only slightly higher than those of non-participants. This is closely related to the fact that the share of individuals who switch occupations is higher among participants. Those who switch occupations tend to start with low wages since they have to start over in a new field where they don't have much experience. Plus, while participants are studying at school, non-participants can keep working, which increase their tenure and in turn, their wages. However, as I showed in the previous section, retraining participants are more likely to work in the non-routine cognitive occupation where the average wage grows more quickly. This is reflected in their wage changes. Wages of participants increase faster with time, making the gap between participants and non-participants wider. Comparing the NLSY79 and 97, wage changes are biggest among recent cohorts, reflecting increased skill and occupation premium.



Note: This figure compares wage changes between retraining participants and non-participants. The vertical axis presents changes in real wages compared to workers' most recent wages prior to unemployment. The horizontal axis shows years after the job loss.

Figure 9: Wage changes

1.3 Model

Time is discrete and lasts forever. There is a unit measure of risk-averse finitely-lived workers. Each worker lives $T \geq 2$ periods deterministically, thus there are T overlapping generations in the economy. A worker's utility in each period is $u(c) + L_\epsilon \eta + \psi \mathbb{1}_{\{\text{retraining}=1\}}$. c is consumption. The function u satisfies $u'(c) \geq 0$ and $u''(c) < 0$. η is the utility from leisure where ϵ denotes the worker's employment status. ψ is workers' preference for studying. This preference parameter captures factors not explicitly modeled here that may affect their retraining participation, such as their learning ability. Workers discount the future at a rate $\beta \in (0, 1)$ and accumulate non-contingent assets denoted as $a \in A = [\underline{a}, \overline{a}] \subset R$. The net rate of return on assets r is taken as given.

Workers are born with skill $s \in \{l, h\}$. Workers born with h represent those who enter the labor market with a college degree, whereas workers born with l represent those who start their careers with only a high-school diploma. In each period, workers with skill s are either employed or unemployed, where the employed value function is denoted E^s and unemployed value function is denoted U^s. Employed workers spend $1 - L_e$ amount of time working and receive wage w each period. They pay a fraction of their wage τw as income tax. Unemployed workers spend $1 - L_u$ searching for jobs and receive unemployment insurance benefit $b > 0$, which expires every period with the probability χ. Once they lose their benefit, they can't receive it again during the same unemployment spell.

There is a continuum of risk neutral firms. Firms belong to either the routine occupation group (denoted by R) or the non-routine cognitive occupation group (denoted by CG). Matching between a skill-s worker and a occupation-j firm produces y_{js} units of output. I assume skill-h workers produce more than skill-l workers and occupation-CG firms produce more than occupation-R firms. Therefore, $y_{CG,h} > y_{R,h} > y_{CG,l} > y_{R,l}$. Matching between skill and occupation is determined exogenously. Skill-s workers meet with occupation-CG firms with the probability p_s. Skill-h workers have a higher chance to be matched with occupation-CG firms than skill-l workers ($p_h > p_l$). Each period, firms post a vacancy at cost κ_{js}. When posting a vacancy, firms offer a contract that specifies the piece-rate of output $\mu \in [0, 1]$ that is paid as wages. A contract is not renegotiable, fixing μ until the match breaks. For simplicity, I assume there is no on-the-job search. The only way to break an existing match is exogenous separation, which happens every period with the occupation and skill-specific probability δ_{js}.

The labor market consists of a continuum of submarkets indexed by worker age t, skill s, occupation j, and the piece-rate μ. Each submarket (t, s, j, μ) has its own tightness $\theta_t(s, j, \mu)$, which is defined as the ratio of vacancies to job applicants. The matching process in each submarket is governed by a constant returns to scale matching function $M(u(t, s, j, \mu), v(t, s, j, \mu))$. Workers' job finding rates are defined as:

$$m(\theta_t(s, j, \mu)) = \frac{M(u(t, s, j, \mu), v(t, s, j, \mu))}{u(t, s, j, \mu)}$$

As $\theta_t(s, j, \mu)$ increases, it becomes easier for workers to find the employer, thus $m'(\theta_t(s, j, \mu)) > 0$. Firms' hiring rates are given as:

$$q(\theta_t(s, j, \mu)) = \frac{M(u(t, s, j, \mu), v(t, s, j, \mu))}{v(t, s, j, \mu)}$$

It becomes harder for firms to find the employee as θ increases, therefore $q'(\theta_t(s, j, \mu)) < 0$. In each labor market, the free entry condition determines the measure of firms. In each period, unemployed workers choose the submarket in which they search for jobs by comparing the wage $w(\theta_t(s, j, \mu)) = \mu y_{js}$ and the probability they get hired $m(\theta_t(s, j, \mu))$.

Low-skill workers can upgrade their skills through retraining. If a skill-l worker is participating in retraining, his value function is scripted with a R, and if not, scripted with a NR. At the beginning of each period, skill-l unemployed workers decide whether they participate in retraining or not by comparing $U^{l,NR}$ and $U^{l,R}$. If they decide to participate, they spend $1 - L_r$ amount of time in retraining for $\overline{z}$ periods. Retraining requires financial and opportunity costs. Participants pay tuition every period, and they are not allowed to work while retraining. I assume participants are still eligible for insurance benefits.[4] The retraining process is stochastic. In each period, participants face a dropout risk. They stop retraining with the probability of $\lambda \in [0, 1]$. Once completing retraining without dropping out, they become skill-h workers, in which case they experience higher wages and higher chances to be matched with a occupation-CG firm.

The government provides unemployed workers with insurance benefits and subsidizes their

[4]In the U.S., unemployment insurance beneficiaries are allowed to enroll in college or job skills training while also receiving benefits as long as they enroll in approved programs (Barr and Turner (2015).)

retraining. ρ fraction of tuition ν is paid by the government. The government finances the retraining costs and insurance benefits by imposing income taxes on employed workers.

In each period, the timeline is given as follows: (1) Existing matches produce and workers are paid. Unemployed workers receive their insurance benefit. (2) Unemployed workers decide whether to participate in retraining or not. (3) Workers choose optimal consumption and saving. (4) Unemployed workers who are not participating retraining choose the submarket in which they search for jobs, and new matches are created. They don't start to produce until the next period. (5) A fraction δ_j of existing matches is separated. Newly formed matches are excluded in this exogenous separation process. (6) A fraction λ of trainees drop out. (7) A fraction χ of unemployed workers lose their unemployment insurance benefit.

1.3.1 Unemployed Workers

In this section, I describe the problem of low-skill unemployed workers. Low-skill unemployed workers decide whether they participate in retraining or search for a job at the beginning of each period. They face a different problem according to their decisions. I describe retraining participants' and non-participants' problems, and unemployed workers' retraining decisions.

1.3.1.1 Retraining Participants The problem of retraining participants is given below:

$$\begin{aligned} U_t^{l,R}(a,b,\psi,j,z) = \max_{a'} u(c,L_r,\psi) &+ \lambda\beta[\chi U_{t+1}^{l,NR}(a',0,\psi,j) + (1-\chi)U_{t+1}^{l,NR}(a',b,\psi,j)] \\ &+ (1-\lambda)\beta[\chi U_{t+1}^{l,R}(a',0,\psi,j,z') + (1-\chi)U_{t+1}^{l,R}(a',b,\psi,j,z')], \quad t \le T \end{aligned} \tag{1.1}$$

$$U_{T+1}^{l,R}(a,b,\psi,j,z) = 0$$

$$\begin{aligned} \text{s.t} \quad & c + a' + (1-\rho)\nu = (1+r)a + b \\ & a' \ge \underline{a} \end{aligned}$$

$z = [z_1, z_2, \cdots, \overline{z}]$ denotes semesters. At each period, retraining participants choose optimal consumption and saving (c and a'), receive insurance benefit b, and pay tuition $(1-\rho)\nu$ where

ρ is the share of tuition paid by the government. Their current utility depends on consumption c, leisure L_r and their preference for studying ψ. In the next period, they drop out with the probability of λ, in which case they fail to upgrade their skills. It is not allowed that retraining participants come back to school at the same period they drop out. With the probability of $1-\lambda$, they go on to the next semester z' and continue retraining.

Each period, χ fraction of benefit recipients lose their benefit. The problem of those who have already lost their benefit is given below:

$$U_t^{l,R}(a,0,\psi,j,z) = \max_{a'} u(c,L_r,\psi) + \lambda\beta U_{t+1}^{l,NR}(a',0,\psi,j) \\ + (1-\lambda)\beta U_{t+1}^{l,R}(a',0,\psi,j,z'), \quad t \le T \quad (1.2)$$

$$U_{T+1}^{l,R}(a,0,\psi,j,z) = 0$$

$$\text{s.t} \quad c + a' + (1-\rho)\nu = (1+r)a + b_{min}$$
$$a' \ge \underline{a}$$

where b_{min} is home production that prevents negative consumption.

The value function of retraining participants takes a different form in the last semester $(z = \overline{z})$. The problem is given below:

$$U_t^{l,R}(a,b,\psi,j,\overline{z}) = \max_{a'} u(c,L_r,\psi) + \lambda\beta[\chi U_{t+1}^{l,NR}(a',0,\psi,j) + (1-\chi)U_{t+1}^{l,NR}(a',b,\psi,j)] \\ + (1-\lambda)\beta\chi[p_h U_{t+1}^h(a',0,CG) + (1-p_h)U_{t+1}^h(a',0,R)] \\ + (1-\lambda)\beta(1-\chi)[p_h U_{t+1}^h(a',b,CG) + (1-p_h)U_{t+1}^h(a',b,R)], \quad t \le T \quad (1.3)$$

$$U_{T+1}^{l,R}(a,b,\psi,j,\overline{z}) = 0$$

$$\text{s.t} \quad c + a' + (1-\rho)\nu = (1+r)a + b$$
$$a' \ge \underline{a}$$

Retraining participants leave school and go on to the labor market in the next period. But with the probability of λ, they fail to complete retraining and search for jobs as low-skilled in the occupation group to which they belonged before they had started retraining. With the probability of $1-\lambda$, they finish retraining with a degree and search for jobs as high-skilled. Those who successfully complete retraining can either search in occupation-CG or occupation-R. It is not guaranteed for them to go into sector-CG, but they have a higher chance to do that. p_h denotes the probability that a skill-h worker searches in occupation-CG.

1.3.1.2 Non-participants The value function of skill-l unemployed workers who are not participating in retraining is given as:

$$
\begin{aligned}
U_t^{l,NR}(a,b,\psi,j) = \max_{a'} u(c, L_u) + \chi\beta[\max_{\mu'} m(\theta_{t+1}(l,j,\mu'))E_{t+1}^l(a',\mu',\psi,j) \\
+ (1-m(\theta_{t+1}(l,j,\mu')))U_{t+1}^l(a',0,\psi,j)] + (1-\chi)\beta[\max_{\mu'} m(\theta_{t+1}(l,j,\mu'))E_{t+1}^l(a',\mu',\psi,j) \\
+ (1-m(\theta_{t+1}(l,j,\mu')))U_{t+1}^l(a',b,\psi,j)], \quad t \leq T \quad (1.4)
\end{aligned}
$$

$$U_{T+1}^{l,NR}(a,b,\psi,j) = 0$$

$$\text{s.t} \quad c + a' = (1+r)a + b \quad \text{and} \quad a' \geq \underline{a}$$

Their utility depends on consumption c and leisure L_u. Besides optimal savings a', workers choose labor markets in which they search for jobs. Since j is determined exogenously, they only choose μ', the contract between a firm and a worker on what fraction of production the worker takes. Choosing μ', they are hired with the probability of $m(\theta(l,j,\mu'))$, in which case, they get paid $w(\theta(l,j,\mu'))$. As mentioned earlier, there exists an inverse relation between $m(\theta(l,j,\mu'))$ and $w(\theta(l,j,\mu'))$ at the equilibrium.

Skill-l unemployed workers make a retraining decision at the beginning of every period:

$$U_t^l(a,b,\psi,j) = \max\left\{U_t^{l,R}(a,b,\psi,j,z_1), U_t^{l,NR}(a,b,\psi,j)\right\} \quad (1.5)$$

Let $D_t(a,b,\psi,j)$ denote the worker's retraining decision. $D_t(a,b,\psi,j) = 1$ when the value of retraining is larger than the value of staying low-skilled ($U_t^{l,R}(a,b,\psi,j,z_1) > U_t^{l,NR}(a,b,\psi,j)$).

1.3.2 Employed Workers

The value function of employed workers is given below:

$$E_t^l(a,\mu,\psi,j) = \max_{a'} u(c, L_e) + \beta[\delta_{js} U_{t+1}^l(a',b,\psi,j) + (1-\delta_{js})E_{t+1}^l(a',\mu,\psi,j)] \tag{1.6}$$

$$E_{T+1}^l(a,\mu,\psi,j) = 0$$

$$\text{s.t} \quad c + a' = (1+r)a + (1-\tau)w(\theta_t(l,j,\mu)) \quad \text{and} \quad a' \geq \underline{a}$$

Employed workers' current utility depends on consumption c and leisure L_e. They choose optimal consumption c and saving a', get paid labor income $w(\theta_t(l,j,\mu))$, and pay income tax $\tau w(\theta_t(l,j,\mu))$. In the next period, with probability δ_{js}, they separate from the firm they are currently working for. For simplicity, I assume there is no on-the-job search, and employed workers don't participate in retraining.

The value functions for skill-h workers are included in the Appendix.

1.3.3 Firms

In each labor market (t,s,j,μ), there's a continuum of firms. Each firm hires a single worker. Firms post a vacancy with a contract that specifies a piece-rate μ of production they pay to their workers. Contracts are renegotiation-proof. An occupation-j firm that hires a skill-s worker produces y_{js} units of output, which represent the matching quality between the firm and the worker. The firm retains a fraction $(1-\mu)$ of the output and pays the rest to the worker. There's no on-the-job search, but the match can break exogenously. The probability that a match between skill-s workers and occupation-j firms exogenously breaks is δ_{js} The value function for firms is given as:

$$J_t(s,j,\mu) = (1-\mu)y_{js} + \beta(1-\delta_{js})J_{t+1}(s,j,\mu), \quad t \leq T \tag{1.7}$$

$$J_{T+1}(s, j, \mu) = 0$$

The free entry condition holds for each submarket (t, s, j, μ). The occupation and skill-specific cost of posting a vacancy, κ_{js}, is equal to the expected benefit of posting a vacancy. This yields:

$$\kappa_{js} = q(\theta_t(s, j, \mu))J_t(s, j, \mu) \tag{1.8}$$

In equilibrium, equation (7) and (8) together yield the market tightness in each submarket:

$$\theta_t(s, j, \mu) = q^{-1}(\frac{\kappa_{js}}{J_t(s, j, \mu)}) \tag{1.9}$$

1.3.4 Equilibrium

An equilibrium in this economy is a set of policy functions for workers $\{c, a', \mu', D\}$, value functions for workers $U_t^s, U_t^{l,NR}, U_t^{l,R}, E_t^s$, value functions for firms J_t, a market tightness function $\theta_t(s, j, \mu)$, an income tax rate τ, and the economy's density function f. These functions satisfy the following:

1. The policy functions solve the workers problems with associated value functions.
2. The free entry condition holds.
3. The total income tax revenue equals the summation of the total amount of unemployment insurance benefit and tuition subsidy
4. The distribution of workers across state is consistent with workers' policy functions.

1.4 Quantitative Analysis

1.4.1 Calibration

In this section, I discuss the parameterization of the model. I divide the model parameters into three groups. For the first set of parameters, I either borrow values from other literature or use standard values. The values of the second set of parameters are chosen directly to match their counterparts in the data. The third set of parameters are jointly calibrated to the U.S. data, to the cohort born 1957-1964. A list of parameters included in each group are summarized in Table 4 and 5.

Parameter	Value	Description	Source
T	140	Life span	Standard
r	0.012	Risk free rate	Annual rate ≈ 5%
β	0.988	Discount factor	1/(1+r)
σ	2	Risk aversion	Standard
$\underline{a}$	-2	Debt limit	Non-binding borrowing constraint
η	0.237	Flow utility of leisure	Herkenhoff et al. (2016)
L_e	0.875	Time spent working	Albanesi and Sahin (2018)
L_u	0.375	Time spent job searching	Albanesi and Sahin (2018)
ζ	0.5	Matching efficiency	Shi (2016)
$\delta_{CG,h}$	0.02	Separation rate at occupation-CG for skill-h	CPS (1983-39)
$\delta_{CG,l}$	0.034	Separation rate at occupation-CG for skill-l	CPS (1983-39)
$\delta_{R,h}$	0.034	Separation rate at occupation-R for skill-h	CPS (1983-39)
$\delta_{R,l}$	0.061	Separation rate at occupation-R for skill-l	CPS (1983-39)
λ	0.08	College dropout rate	NLSY97
p_h	0.7347	Prob that a type-h works at the NRCG occupation	CPS (1983-89)
p_l	0.2183	Prob that a type-l works at the NRCG occupation	CPS (1983-89)
M_h	0.2508	Fraction born as type-h	CPS (1983-89)
b	0.32	UI benefit	Benefit income ratio ≈ 40%
χ	0.788	UI benefit expiration rate	Expected UI duration ≈ 26 weeks

Table 4: Independently chosen model parameters

The length of a period is calibrated to a quarter, and the model age zero corresponds to age 18 in the data. The workers leave the model at the model age of 140. All workers enter the model unemployed and with zero assets. I assume a quarterly interest rate equal to 1.2%, which yields an annual rate of 5%. Workers are born as either skill-l or skill-h. The fraction born as skill-h, M_h, is set to the share of college graduates at age 23 in the Current Population Survey (CPS). Unemployed workers search for jobs either in occupation-CG or occupation-R. The fraction of skill-s workers who search in occupation-CG, p_s, is chosen to match the share of each skill type (college graduates or high-school graduates) in the non-routine cognitive occupation calculated from the CPS.

Parameter	Value	Description
$\mathrm{y}_{CG,h}$	1.39	Matching quality between occupation-CG and skill-h
$\mathrm{y}_{R,h}$	1.156	Matching quality between occupation-R and skill-h
$\mathrm{y}_{CG,l}$	1.128	Matching quality between occupation-CG and skill-l
$\mathrm{y}_{R,l}$	1	Matching quality between occupation-R and skill-l
$\kappa_{CG,h}$	0.6481	Vacancy posting cost at occupation-CG for skill-h
$\kappa_{R,h}$	0.3104	Vacancy posting cost at occupation-R for skill-h
$\kappa_{CG,l}$	0.3932	Vacancy posting cost at occupation-CG for skill-l
$\kappa_{R,l}$	0.2772	Vacancy posting cost at occupation-R for skill-l
ψ_μ	0.2701	Scale parameter in the preference distribution
ν	0.092	Tuition

Table 5: Jointly-calibrated parameters

Preferences for workers at a given period are given below:

$$u(c, L_\epsilon, \psi) = \frac{c^{1-\sigma} - 1}{1-\sigma} + \eta(1 - L_\epsilon) + \psi \mathbb{1}_{\{\text{retraining}=1\}}, \quad \text{where} \quad \epsilon = e, r, u \tag{1.10}$$

The discount factor, β, is set to 0.988 so that $\beta = 1/(1+r)$. The risk aversion parameter, σ, is set to a standard value, 2.

The utility from leisure, η, is set to 0.237 following Herkenhoff et al. (2016). L_e is set to 0.625 (10 hours of work out of 16 active hours) and L_u to 0.125 (2 hours of job searching for jobs out of 16 active hours) following Albanesi and Şahin (2018) and Krueger and Mueller (2012).

I assume that retraining participants spend as much time at school as employed workers spend at work. Thus, $L_r = L_e$.

The utility from studying, ψ, is 6 evenly spaced grid points over [0.6,1.4]. Low-skill workers are born with a draw over this grid. The drawing process follows the exponential distribution, and the scale parameter of the distribution, ψ_μ, is calibrated to match the mean retraining rate from the NLSY79.

The unemployment insurance benefit b is chosen so that it replaces about 40% of prior earnings. The income tax rate, τ, is set to the value that makes the government's budget balance. The benefit expiration rate, χ, is chosen so that the expected duration of eligibility is approximately 26 weeks. Home production, b_{min}, when the benefit is not available, is set to the value that prevents negative consumption.

The occupation and skill-specific production, y_{js}, is calibrated to match the college premium in each occupation and the non-routine cognitive premium among each education group. The premiums are obtained from the CPS.

To assign values to δ_{js}, the occupation and skill-specific job separation rate, and κ_{js}, the occupation and skill-specific job posting cost, I calculated the gross worker flows from the CPS using its panel structure. The CPS surveys the same household 4 months consecutively, skip 8 months, and then re-surveys for another 4 months. I restricted the sample to the households that are surveyed for the first time and the households that just come back to the survey after the break so that I can observe their employment status three months later. I calculated the quarterly job separation rate in occupation-j for skill-s workers as the fraction of employed skill-s workers in occupation-j who became unemployed three month later. I assign these values to δ_{js} in the model. Similarly, I calculated the quarterly job finding rate in occupation-j for skill-s workers as the fraction of unemployed skill-s workers who previously held a occupation-j job and became employed three months later. κ_{js} is calibrated to match these values.

Retraining takes 9 model periods (3 years assuming participants spend 3 quarters per year at school). The dropout rate, λ, is chosen to match the retraining completion rate from the NLSY97. The tuition, ν, is chosen to match the tuition in the data as a ratio of the average wages. To calculate the tuition-income ratio, I use in-state tuition data from the National

Center for Education Statistics (NCES) and the average annual income among high-school graduates from the CPS. The tuition subsidy, ρ, is set to zero in the benchmark calibration since public-sponsored retraining programs are very limited.[5] In the later part of the paper, I adjust this parameter to examine the effects of subsidizing retraining.

I use a constant returns to scale matching function that yields well-defined probabilities following Schaal (2012):

$$M(u,v) = \frac{uv}{(v^{\zeta} + u^{\zeta})^{\frac{1}{\zeta}}} \tag{1.11}$$

The firms' hiring rates are given by $q(\theta_t(s,j,\mu)) = \frac{M(u_t(t,s,j,\mu),v_t(t,s,j,\mu))}{v_t(t,s,j,\mu)}$, and the workers' job finding rates are given by $m(\theta_t(t,s,j,\mu)) = \frac{M(u_t(t,s,j,\mu),v_t(t,s,j,\mu))}{u_t(t,s,j,\mu)}$. The matching elasticity, ζ, is set to 0.5 as in Shi (2016).

1.4.2 Model Performance

Table 6 compares targeted moments between the model and the data. The statistics generated by the model are very close to those obtained from the data. Figure 10 graphically shows the model prediction of retraining rates by age. The model replicates retraining rates in the NLSY79 well for younger population but underpredicts retraining rates for older population. One possible explanation is that the model only takes account of economic aspects of retraining whereas in reality, people decide to go back to school for other reasons such as in search for a sense of accomplishment or the pure joy of learning. Such non-economic motivations can play a more important role in explaining older workers' retraining participation because a college degree may not be worthwhile for them in terms of career advancement.

[5] The Workforce Investment Act was introduced in 1998. Public-sponsored retraining before 1998 was provided through Job Training Partnership Act, which focused more on supporting the economically disadvantaged than retraining unemployed workers (Jacobson et al., 2005b). Even with WIA, public-sponsored retraining is limited. The sequential nature of the program may mean that not many unemployed workers never reach the training level of services(Frank and Minoff, 2005).

	Model	Target	Source
Skill premium in occupation-CG	28.21%	28.42%	CPS (1983-89)
Skill premium in occupation-R	25.60%	25.80%	CPS (1983-89)
occupation premium for skill-h	23.22%	19.37%	CPS (1983-89)
occupation premium for skill-l	20.72%	19%	CPS (1983-89)
Job finding rates at occupation-R for skill-l	44.31 %	45.14%	CPS (1983-89)
Job finding rates at occupation-R for skill-h	48.64%	48.94%	CPS (1983-89)
Job finding rates at occupation-CG for skill-l	47.97%	48.69%	CPS (1983-89)
Job finding rates at occupation-CG for skill-h	45.22%	44.93%	CPS (1983-89)
Tuition-income ratio	9.97%	10.81%	NCES, CPS (1983-89)
UI benefit-income ratio	39.88%	40%	Standard
Retraining population (23-33)	1.66%	1.66%	NLSY79

Table 6: Targeted moments

In the empirical analysis section, I documented that the NLSY97 cohorts have a considerably higher retraining rate than the NLSY79 cohorts. As a further test of the calibration, I see if the model can replicate this. I compare retraining rates of two groups of workers who face different labor markets in terms of wage premium and job transition rates. One group is thrown into a similar labor market that the NLSY79 cohorts (born 1957-1964) experienced when they were young workers. The other group is given the labor market conditions that the NLSY97 cohorts (born 1980-1984) faced early in their career.

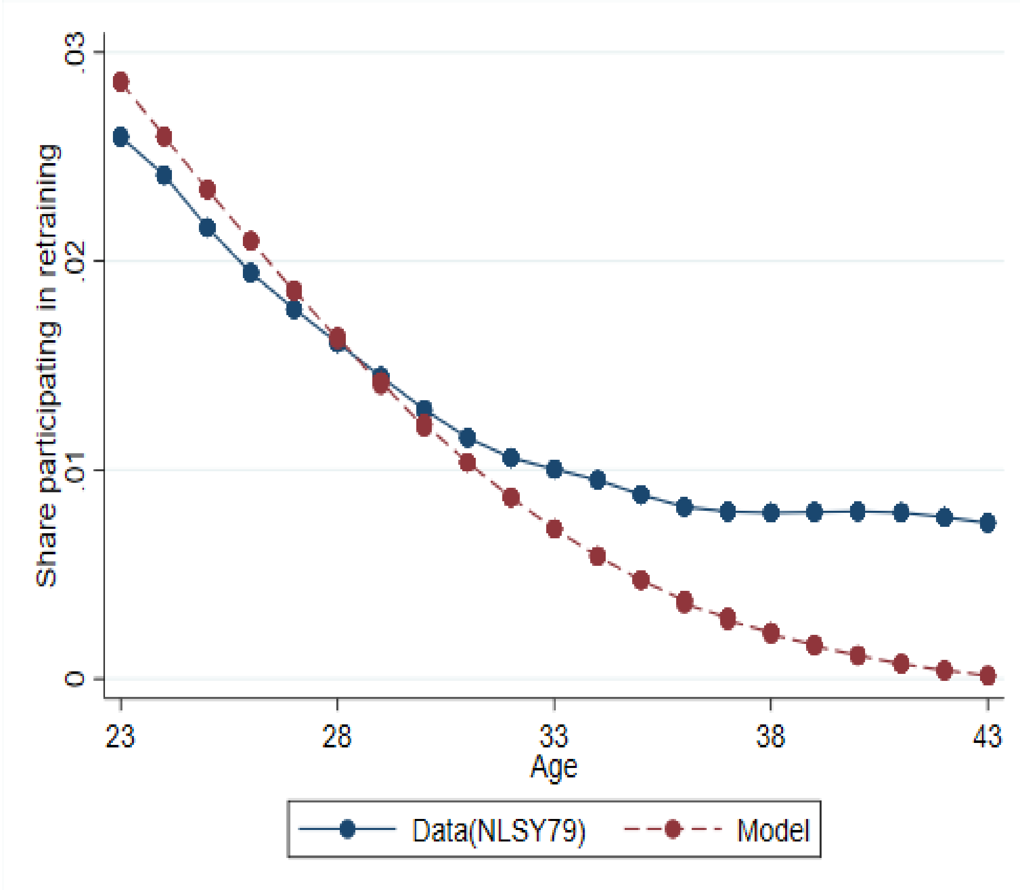


Figure 10: Model fit

The NLSY79 and NLSY97 cohorts have quite different labor market experiences. Table 7 compares some of the labor market characteristics that the two cohorts faced. The younger cohorts enjoyed a higher college premium and a higher non-routine cognitive occupation premium. However, they also suffered a worse labor market, featured as a lower job finding rate and a higher job separation rate. This is more prominent among low-skill workers. Some of it has to do with the fact that the economy has not yet fully recovered from the great recession when the younger cohort started their career. However, the fact that low-skill workers suffered a bigger drop in the job finding rate and a bigger rise in the job separation rate than high-skill workers reflects the gradual decline of routine jobs in the U.S. caused by automation and international trade.

	1957-1964 cohorts	1980-1984 cohorts
College premium (occupation-CG)	28.42%	43.29%
College premium (occupation-R)	25.80%	36.09%
occupation premium (skill-h)	19.37%	30.78%
occupation premium (skill-l)	19%	24.38%
Job finding rates (occupation-CG & skill-h)	44.93%	35.28%
Job finding rates (occupation-CG & skill-l)	48.69%	28.49%
Job finding rates (occupation-R & skill-h)	48.93%	35.92%
Job finding rates (occupation-R & skill-l)	45.14%	28.15%
Job separation rates (occupation-CG & skill-h)	2%	2.9%
Job separation rates (occupation-CG & skill-l)	3.4%	4.68%
Job separation rates (occupation-R & skill-h)	3.4%	4.28%
Job separation rates (occupation-R & skill-l)	6.1%	6.89%
Tuition/Income	10.81%	27.02%
Share of college graduates at age 23	25.08%	36.65%

Note: Tuition includes tuition and required fee, averaged between four-year and two-year colleges.
Income is the average annual income among high-school graduates.
Source: CPS

Table 7: Comparison of labor market characteristics between two cohorts

The benchmark calibration features the labor market for the older cohort. Starting from there, I generate changes in the labor market characteristics that I observed in the data and see the resulting effects on retraining. I adjust matching quality differences across skill-occupation pairs (y_{js}) to reflect the rise of the skill and cognitive occupation premium. The substantial growth of these premiums increases benefits of retraining. In addition, I change parameters associated with job transition rates to match disproportionate changes in job finding and separation rates across skill-occupation pairs. Specifically, I adjust δ_{js} to match occupation and skill-specific job separation rates. I then vary κ_{js}, the vacancy posting cost, to match occupation and skill-specific job finding rates. Compared to the older cohort, the younger cohort, notably those without college education, faced a lower job finding rate and a higher job separation rate. These changes in job transition rates give low-skill workers another reason to retrain: career prospects without retraining look dim. I also vary tuition (ν) and the fraction of workers born as high-skill (M_h). It is well known that college tuition in the U.S. has risen significantly, and this increases the cost of retraining. I change the initial skill distribution as well to reflect the fact that the number of individuals who go straight to college from high school is higher among the younger cohort.

In the data I observe a higher retraining rate for the younger cohort than for the older cohort. Retraining rates among the younger cohort is about 6.52 percent compared to 1.66 percent among the older cohort. Adjusting for the labor-market related parameters mentioned above, the model yields retraining rates of 5.51 percent, predicting about 79 percent of the difference in retraining participation between the two cohorts observed in the data.

To further investigate the sources of higher participation in retraining among the younger cohort, I decompose the difference in retraining rates between the two cohorts into the contributions of each change in the labor market. To this end, I adjust one set of parameters at a time. For example, to see the contribution of wage premium, I adjust y_{js} to the values associated with the younger cohort with the rest of the parameters fixed at the level associated with the older cohort. Tuition and initial skill distribution are fixed at the level of the younger cohort.

Table 8 presents the results. The decrease of job finding rates for low-skill workers cause the largest rise in retraining. The increase of skill and occupation premium generates the second-largest rise. These results suggest that low-skill workers retrain not only to get paid more but also to escape from the occupation in decline. There are factors that curb retraining as well. The increase of job separation rates for low-skill workers causes a modest decline in retraining. The decrease of job finding rates and the increase of job separation rates for high-skill workers decrease retraining by reducing the benefit of being high-skilled.

	Retraining population (%)		
	1957-1964 cohorts	1980-1984 cohorts	Differences(pp)
Data	1.66	6.52	4.86
Model: all	1.66	5.51	3.85
Model: skill and occupation premium only	1.66	3.11	1.44
Model: job finding rates (High-skill) only	1.66	0	-1.66
Model: job finding rates (Low-skill) only	1.66	6.56	4.9
Model: separation rates (High-skill) only	1.66	0	-1.66
Model: separation rates (Low-skill) only	1.66	0.34	-1.32

Note: Tuition and the fraction born as high-skill are set to match the level for the younger cohort.

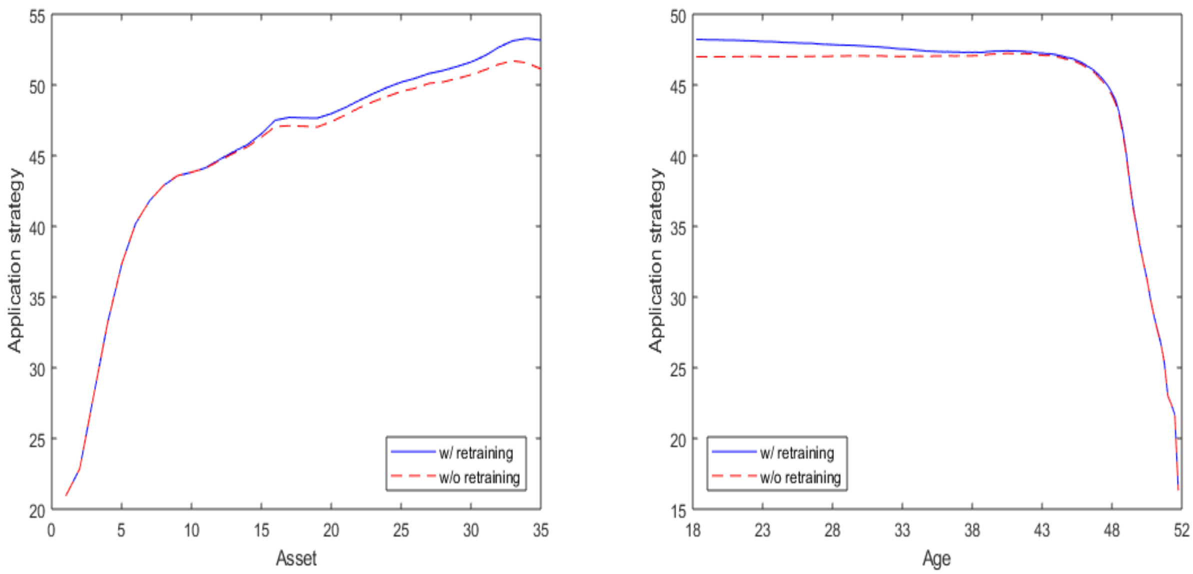
Table 8: Retraining rates, in the data and as predicted by the calibrated model

1.4.3 Counterfactual

In this section, I examine the aggregate effects of retraining on economy. I compare the benchmark economy to a counterfactual economy where retraining is not possible and see how retraining affects wage inequality and welfare.

1.4.3.1 Retraining and Wage Inequality First, I look into the relationship between retraining and wage inequality. Retraining affects wage inequality by changing workers' optimal search strategies. In my model, unemployed workers face a trade-off between high wages and high job finding rates when they decide which jobs to apply for. In general, wealthy workers apply for high-paying but hard to obtain jobs since their wealth allows them to endure a longer unemployment duration. Retraining intervenes in this process by increasing the value of unemployment. The possibility of retraining makes unemployment less painful by giving unemployed workers one more option. This enables unemployed workers to make bolder choices when they apply for jobs. As a result, unemployed workers apply for higher-paying jobs at a given amount of assets. Figure 11 presents low-skill unemployed workers' job application strategies by assets. The vertical axis represents job quality. The higher the number, the higher the wage and the lower the job finding rate. It shows that there exists a positive correlation between asset holdings and job quality, consistent with Eeckhout and Sepahsalari (2014) and

Chaumont and Shi (2017). It also shows that, at a given level of assets, workers apply for better jobs in the benchmark economy where retraining is possible than they do in the counterfactual economy where there is no retraining.



Note: This figure plots low-skill unemployed workers' optimal job search strategies by asset holdings (left) and by age (right). Higher numbers in the vertical axis represent higher-paying, harder to obtain jobs. The solid line shows job search strategies of the model with retraining. The dashed line shows job search strategies of the model without retraining.

Figure 11: Job search strategies

This interaction between retraining and directed job search affects unemployed workers' re-employment wages. Table 9 compares the mean model wage among three different economies: the benchmark economy, a counterfactual economy where retraining doesn't exist, and another counterfactual economy where retraining completion rate is higher than it is in the benchmark economy. This economy can be considered as an economy that has a more effective retraining system than the benchmark economy. It has the highest retraining rates among the three economies.

	Model w/ retraining	Model w/ retraining	Model w/o retraining
	$\lambda = 0.04$	$\lambda = 0.08$	
High-skill	1.1261	1.1256	1.1253
Low-skill	0.8481	0.8025	0.7987
All	1.0042	0.8979	0.8844

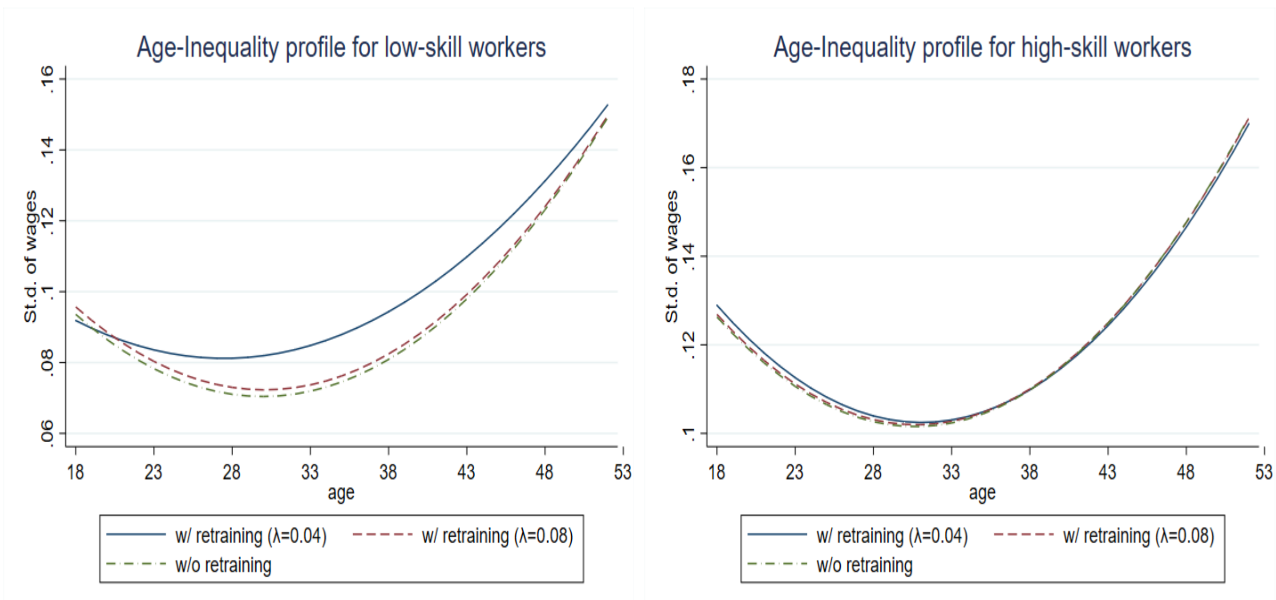
Note: This table reports the model predicted mean wages for high- and low-skill workers. λ is the dropout rate.

Table 9: Model predicted mean wages

Compared to the economy without retraining, the mean wage of low-skill workers is 0.5% higher in the benchmark economy and 6% higher in the economy with a high completion rate. This result is consistent with the mechanism explained above. Workers go for higher-paying jobs when there is a retraining channel, and therefore, get paid better. The mean wage of high-skill workers shows a similar pattern. The mean wage of high-skill workers is 0.03% higher in the benchmark economy and 0.08% higher in the economy with a high completion rate compared to the no-retraining economy. Even though high-skill workers are not directly affected by retraining rates, their wages are indirectly affected through the number of high-skill workers in the economy and corresponding income tax revenue. As fewer workers participate in retraining, fewer high-skill workers are created, and therefore, the income tax revenue decreases. Consequently, the income tax rate goes up, and after-tax wages decrease for high-skill workers. Although the mean wage increases for both skills, it increases more among low-skill workers, making the wage-gap between low- and high-skill workers shrink. The high-skill premium decreases from 40.9% in the no-retraining economy to 40.3% in the benchmark economy and to 32.8% in the economy with a high completion rate.

On the other hand, retraining makes the wage distribution within each skill group more dispersed. Figure 12 plots age-inequality profiles by education level. The wage standard deviation predicted from the model is smaller than that from the data, mainly because the model lacks employment-to-employment transition resulting in less variability in employment history. However, the model replicates the U-shape in the data well. The wage standard deviation is high among young workers. As they accumulate assets and gradually move to high-paying jobs, their wages converge. This leads to the initial reduction in the wage standard deviation.

As workers get older, they start to have very different employment histories, which leads to the rise in the wage standard deviation. Table 10 reports the standard deviation of wages of the three economies. Compared to the no-retraining economy, the wage standard deviation is 0.08% higher for high-skill workers and 9.1% higher for low-skill workers in the economy with a high completion rate. The wage standard deviation among high-skill workers is higher in the benchmark economy because of newly-created high-skill workers. High-skill workers who just finished retraining tend to own lower levels of assets since they ran down their savings while retraining. To avoid extended unemployment, they apply for low-paying, easily attainable jobs, stretching the left end of the wage distribution. Similarly, the wage variance among low-skill workers is higher in the benchmark economy since retraining participants who drop out are likely to end up at the lower tail of the wage distribution.



Note: This figure plots the standard deviation of wages by age. The left figure is for low-skill workers, and the right figure is for high-skill workers.

Figure 12: Age-inequality profiles by skill

In summary, as more workers participate in retraining, between-skill inequality decreases, and within-skill inequality increases.

	Model w/ retraining	Model w/ retraining	Model w/o retraining
	$\lambda = 0.04$	$\lambda = 0.08$	
High-skill	0.1203	0.1202	0.1202
Low-skill	0.0995	0.0926	0.0912
All	0.1736	0.18	0.1760

Note: This table reports the model predicted mean wages for high- and low-skill workers. λ is the dropout rate.

Table 10: Model predicted st.d. of wages

1.4.3.2 Retraining and Welfare In this section, I examine the effects of retraining on workers' welfare. I assume the agents in the benchmark economy are transferred to a counterfactual economy where retraining is not possible. Then I calculate consumption equivalent, the remaining lifetime consumption that makes agents indifferent between the two economies. Everything else is the same between the two economies except the income tax rate. The income tax rate is higher in the counterfactual economy. The lack of retraining in the counterfactual economy leads to a smaller tax revenue because fewer high-skill workers are created. To keep the government budget balanced, the income tax rate should rise by about 4.5 percent.

The results of the welfare analysis is given in table 11. Moving to the economy without retraining decreases welfare by about 1.5 percent of consumption on average. All workers in the benchmark economy are worse-off. For high-skill workers, welfare losses come exclusively from income tax increases. For low-skill workers, on the contrary, the losses come from several other sources as well as income tax increase. First, eliminating retraining alters workers' job application strategies. As I discussed in the previous section, with a lack of retraining, unemployed workers would rather go for low-paying, easily attainable jobs. This decreases their re-employment wages but increases their chances of finding a job. The effects on welfare are ambiguous. Second, in the counterfactual economy, workers tend to save less because they do not have to save money to retrain in the future, and also they do not have to hold as much precautionary savings as they face shorter unemployment duration by making safe application choices. This channel can have positive effects on welfare by increasing consumption. The last source of welfare changes is their lost opportunities to upgrade skills.

Age	Asset	Low-skill			High-skill	
		Employed	Unemployed		Employed	Unemployed
			Non-participants	Participants		
18-22	1st quartile	-0.0143	-0.0047	-0.0022	-0.0247	-0.0072
	2nd quartile	-0.0267	-0.0052	-0.0018	-0.0023	-0.0067
	3rd quartile	-0.0190	-0.0011	-0.0079	-3.1389e-04	-0.0025
	4th quartile	-0.1476	-0.0011	-0.0370	-1.8505e-04	-0.0048
23-27	1st quartile	-0.0053	-0.0018	-0.0032	-0.0014	-0.0028
	2nd quartile	-0.0291	-0.0014	-0.0025	-5.6435e-04	-0.0130
	3rd quartile	-0.0027	-3.4600e-04	-0.0143	-6.5554e-04	-0.0022
	4th quartile	-0.1840	-9.5811e-04	-0.1142	-4.0890e-04	-0.0084
28-32	1st quartile	-0.0049	-0.0017	-0.0015	-8.4848e-04	-0.0021
	2nd quartile	-0.0281	-0.0012	-0.0013	-0.0063	-0.0113
	3rd quartile	-4.4161e-04	-7.6116e-05	-0.0072	-7.9607e-04	-0.0025
	4th quartile	-0.0760	-3.5574e-04	-0.0559	-5.3898e-04	-0.0139
33-37	1st quartile	-0.0048	-0.0017	-4.5502e-04	-5.3898e-04	-0.0020
	2nd quartile	-0.0276	-0.0012	-4.3900e-04	-3.5669e-04	-0.0227
	3rd quartile	-1.2494e-04	-1.3804e-05	-0.0029	-6.6452e-04	-0.0028
	4th quartile	-0.0200	-6.5512e-05	-0.0197	-0.0026	-0.0345
38-42	1st quartile	-0.0047	-0.0017	-2.3178e-05	-7.9252e-04	-0.0027
	2nd quartile	-0.0231	-0.0012	-5.5142e-05	-1.6039e-04	-0.0044
	3rd quartile	-0.0029	-1.9182e-04	-6.4491e-04	-1.6283e-04	-0.0023
	4th quartile	-0.0101	-1.3065e-04	-0.0045	-0.0049	-0.0518
43-47	1st quartile	-0.0024	-7.7524e-04	-0.001	-7.0516e-05	-0.0011
	2nd quartile	-0.0105	-8.9856e-04	0.000	-5.7326e-05	-0.0017
	3rd quartile	-0.0052	-5.9124e-04	0.000	-5.0750e-04	-0.0044
	4th quartile	-0.0522	-8.0435e-04	-2.7976e-05	-0.0079	-0.1353
48-52	1st quartile	-1.7700e-04	-4.5964e-05	-2.6039e-04	-5.0107e-06	-2.7928e-05
	2nd quartile	-3.9793e-04	-3.3950e-05	0.000	-3.6889e-06	-5.9363e-05
	3rd quartile	-0.0136	-3.7167e-04	0.000	-6.7562e-05	-0.0046
	4th quartile	-0.0535	-6.1823e-04	0.000	-6.0750e-04	-0.0210
	Overall	-0.7694	-0.0302	-0.2780	-0.0593	-0.3689
		-1.506				

Note: This table presents welfare changes from getting rid of retraining by age, asset, employment status, and education level.
Results reported as change(%) in the remaining lifetime consumption relative to the benchmark economy.

Table 11: Welfare changes

To understand the direction and magnitude of each effect, I decompose the welfare changes from eliminating retraining according to the channels suggested above. To this end, I block each channel in turn and calculate the welfare changes again. Specifically, I assume that the policy functions or parameters associated with the channel in interest are fixed at their benchmark level and re-calculate the value functions in the counterfactual economy. For instance, to see the effects coming through workers' optimal search strategies, I assume a worker in the counterfactual economy chooses the same firm he would have chosen in the benchmark economy. Column 2 in Table 12 shows welfare changes for low-skill workers with the tax effects excluded. The average welfare losses increased from -1.078 to -0.761 percent. Column 3 in Table 12 reports the results when the firm choice effects are excluded. Column 4 in Table 12 shows the case where the saving effects are removed. The average welfare decreases even more when the search strategy effects and the saving effects are not taken account of, implying that these two channels offset some of the losses from losing retraining. Overall, the tax, search strategy, and saving effects together account for about 25 percent of the total welfare losses. The rest comes from lost opportunities to upgrade skills. The contribution of each channel is different according to workers' employment status. Changes in income tax, optimal search strategies, and optimal savings explain around 35 percent and 42 percent of the welfare losses for the employed and non-participants, respectively. However, they barely explain the welfare losses of retraining participants, suggesting most of their losses come from their lost chances to upgrade skill. It is not surprising since they are the most likely to become high-skill workers.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Employed	-0.769	-0.475	-0.779	-0.786
Non-participants	-0.030	-0.009	-0.035	-0.034
Participants	-0.278	-0.277	-0.283	-0.281
All	-1.078	-0.761	-1.097	-1.101

Note: Scenario 1: All effects considered, i.e., No decomposition.
Scenario 2: Tax effects excluded.
Scenario 3: Firm choice effects excluded.
Scenario 4: Saving effects excluded.
The detailed welfare over asset and age can be found in Table 28-30.

Table 12: Welfare changes for low-skill workers (decomposed)

1.4.4 Policy Implications

I now turn my attention to policy analysis. Government policies in the benchmark economy resembles unemployment policies of the US; they are more focused on passive labor-market policies such as insurance benefit rather than active market policies such as retraining. In this section, I use my model of retraining to simulate alternative policy scenarios where the government is more actively involved in retraining and explore their macroeconomic effects on the economy.

I compare five policies, all of which aim to encourage retraining among low-skill unemployed workers. The policy alternatives I consider are as follows. (1) government pays all the retraining costs. (2) retraining participants can receive unemployment benefit for a longer period of time than non-participants. (3) retraining participants can receive higher unemployment benefit than non-participants.[6] (4) there is no unemployment insurance benefit, and retraining costs are fully covered by government. (5) government pays retraining costs only for selected population (older and/or low-asset) who are the most reluctant to retrain. These polices are compared to the benchmark economy where unemployed workers retrain at their own expenses. Under all policies, the government budget is balanced.

Table 13 presents the main aggregate statistics in the steady states of economies imple-

[6]Policies (2) and (3) are inspired by the German system, as discussed in (Nie, 2010).

menting different policies in comparison to the benchmark economy. I find that universal free retraining results in the highest retraining participation for unemployed workers. However, it comes with a cost of high taxes; about 27% increase in taxes on labor income is needed to guarantee free training for all participants. From the perspective of cost effectiveness, combining retraining participation with higher insurance benefit yields the best outcome. It achieves an increase of 1.43 percentage point in retraining. The income tax rate decreases by 9.17 percent. It is the policy that maximizes the average welfare as well. It increases the average welfare by 3.11 percent.

Although the average welfare of both high- and low-skill workers is the highest under the policy where retraining participants can receive higher unemployment insurance benefit, the welfare ordering of policies is not the same between the two skill groups. Since high-skill workers only care about the tax burden they are going to carry, they prefer policies that yield smaller tax increase than others, whereas low-skill workers consider the benefits and costs of retraining as well as income tax. For instance, low-skill workers will choose free retraining with no insurance benefit over combining retraining participation with longer duration of benefit receipt even though it comes with higher income tax.

One thing I want to point out here is that all of the policies suggested above would be more effective if they were implemented along with actions that improve retraining completion rates. Some of above polices yield considerable tax increases mainly because not many retraining participants translate into high-skill workers, only increasing the number of new taxpayers by so much. With a higher completion rate, increased government spending will be partly offset by increased tax revenue, and therefore the tax increase will not be as large. Since financial difficulties are one of the most common reasons of discontinuing college education, it is true that above policies can affect participants' decisions to drop out. Unfortunately, my model is not able to capture that since dropping out is considered as an exogenous shock. It will be an interesting extension to allow retraining participants to decide whether to continue retraining.

	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5
Tax	27.22	-6.42	-9.17	1.33	9.50
Retraining Rate	5.44	1.43	1.43	5.41	3.33
Between-skill Inequality	-3.75	-1.18	-1.63	-4.27	-3.27
Within-skill Inequality (High)	2.14	0.58	0.58	6.41	7.12
Within-skill Inequality (Low)	6.77	3.34	3.11	8.01	7.54
Welfare (Overall)	-5.02	2.41	3.11	-1.87	0.82
Welfare (High)	-5.91	1.50	1.66	-2.80	-1.99
Welfare (Low)	0.89	0.90	1.45	0.94	0.82

Note: Policy 1: Government pays all the retraining costs.
Policy 2: Retraining participants can receive unemployment benefit for a longer period of time than non-participants (up to two years).
Policy 3: Retraining participants can receive higher unemployment benefit than non-participants
Policy 4: No UI benefit + free retraining
Policy 5: Government pays retraining costs only for selected population (older and/or low-assets)
Results reported as percent change (percentage point change in case of retraining rate) relative to the benchmark scenario. The detailed welfare over asset and age can be found in Table 31-32.

Table 13: Comparison of unemployment policies

1.5 Conclusion

In this paper, I develop an overlapping-generations model featuring retraining and directed job search to study the macroeconomic effects of retraining. Low-skill unemployed workers in the model either search for jobs or participate in retraining. Retraining is stochastic. Conditional on successfully completing retraining, participants can get better-paying, more highly-skilled jobs. Non-participants decide which job to apply for by comparing wages against job finding rates. Wealthy workers apply for high-paying but hard to obtain jobs since they can survive long unemployment duration.

I use the model to examine the effect retraining has on wage inequality and welfare. Retraining affects wage inequality by changing unemployed workers' job search strategies. It increases the value of unemployment and makes unemployed workers seek higher-paying jobs at a given asset level. As a result, re-employment wages increase for low-skill workers, and the between-skill inequality reduces. Retraining also affects wage inequality indirectly through workers' wealth. Newly-created high-skill workers and retraining participants who don't finish retraining tend to hold a small amount of assets.Therefore, they go for low-paying but easily attainable jobs. The constant flow into the lower tail of the wage distribution increases the within-skill inequality.

Eliminating the retraining channel in the benchmark economy makes everyone worse off. It yields welfare losses equivalent of 1.5 percent decrease in consumption. The welfare losses come from income tax increases, changes in optimal firm choices, changes in saving, and lost opportunities to upgrade skills. The first three channels account for about 25 percent of the average welfare losses. But they don't explain much of welfare losses for retraining participants, implying their losses mainly come from the lost chances to become high-skill workers.

I use the model to evaluate labor-market policies that aim to encourage retraining participation. I compare changes in retraining rates, tax increase, and welfare across policies. I show that combining retraining with more generous unemployment insurance benefit is the best policy in terms of cost-effectiveness and welfare.

2.0 Gender Gap in Retraining[1]

2.1 Introduction

As automation has declined economic opportunities for less-educated workers, getting college education becomes more important to have a more stable career path. However, working toward a college degree at the start of someone's working life does not seem to be enough to maintain their career. Prolonged working lives and rapid changes at the workplace could require workers who already have a college degree to constantly upgrade skills throughout their careers.

The number of workers who pursue further education later in life has increased. However, there exist gender disparities in the share of workers who do that. Figure 13 shows the share of people at each age group who participate in any kind of education or training programs, ranging from on-the-job training to a college education. The share is higher for women regardless of age. It is especially pronounced among the relatively younger population, those in their late twenties.

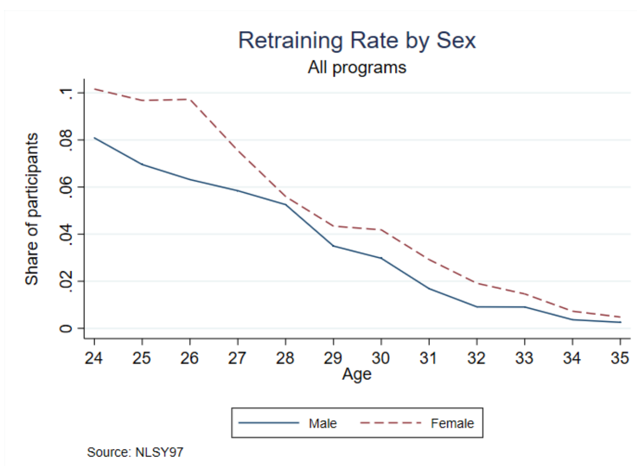


Figure 13: Retraining rate by sex

Over the last three decades, we observe emerging gender gaps that favor women along with

[1]This chapter is coauthored with Stefania Albanesi

many dimensions including college enrollment to real wages levels. Figure 13 implies that this pattern is also shown in lifelong education. It puts a concern that men may not be adjusting to the rapidly changing labor market as well as women do. As lifelong education becomes more important, understanding the source of the relative success of a certain demographic group can help policymakers to design programs to encourage other groups to catch up.

In this paper, we document the evolution of the gender gap in retraining and provide empirical evidence of what causes it. We propose hypotheses that can possibly explain the phenomenon and explore each hypothesis one by one. Specifically, we address gender differences in social skills, occupation distribution, spouses' employment status and wages, and the impact of automation.

Several studies (Deming, 2017; Cortes et al., 2018) document that the demand for social skills has increased in high-end occupations. A wider range of tasks required in such occupations makes workers' social skills more valuable because higher social skills make it easier for workers to specialize in tasks they are good at and trade with co-workers. The high reward for social skills encourage workers who possess high social skills to invest more in education, which will give them access to high-end occupations. If women have relatively higher social skills than men, as many psychological and neuroscientific studies suggest, it could lead to women's higher participation in retraining.

We address this hypothesis by examining the relationship between participants' social skills and the benefits of retraining. Using the National Longitudinal Survey of Youth 1997, we find that the return to retraining measured by hourly wages increases as participants' social skills increase. This boosting effect of social skills on the gain of retraining does not differ by participants' gender, implying that women's higher retraining rates derive from the composition effects.

The rest of the paper is devoted to examining alternative explanations. We address possibilities that women dominating professions offer greater encouragement and support for continued learning, that a higher fraction of second-earners and higher spouse wages among women cause more women to retrain, and that women's fewer work opportunities in non-college occupations drive them into seeking more education.

2.2 Data

Our main data source is the 1997 National Longitudinal Survey of Youth (NLSY97). The NLSY97 tracks those who were born between 1980 and 1984 from the year of 1997. The survey was done on an annual basis until 2010 and switched do a biannual basis after.

Since our interest is in workers who pursue education later in life, we restrict the sample to those who are over the age of 23. We exclude respondents who have less than a high school education. Respondents who have military experience are also discarded.

The NLSY97 provides monthly schooling and training information not only for those who are school age but also for the older population. Figure 14 breaks retraining down into specific programs. It shows that more than half of the workers who seek further education or training do so through a college education. The share of short-term vocational training and on-the-job training, which are considered as traditional retraining programs, is much smaller than that of a college education.

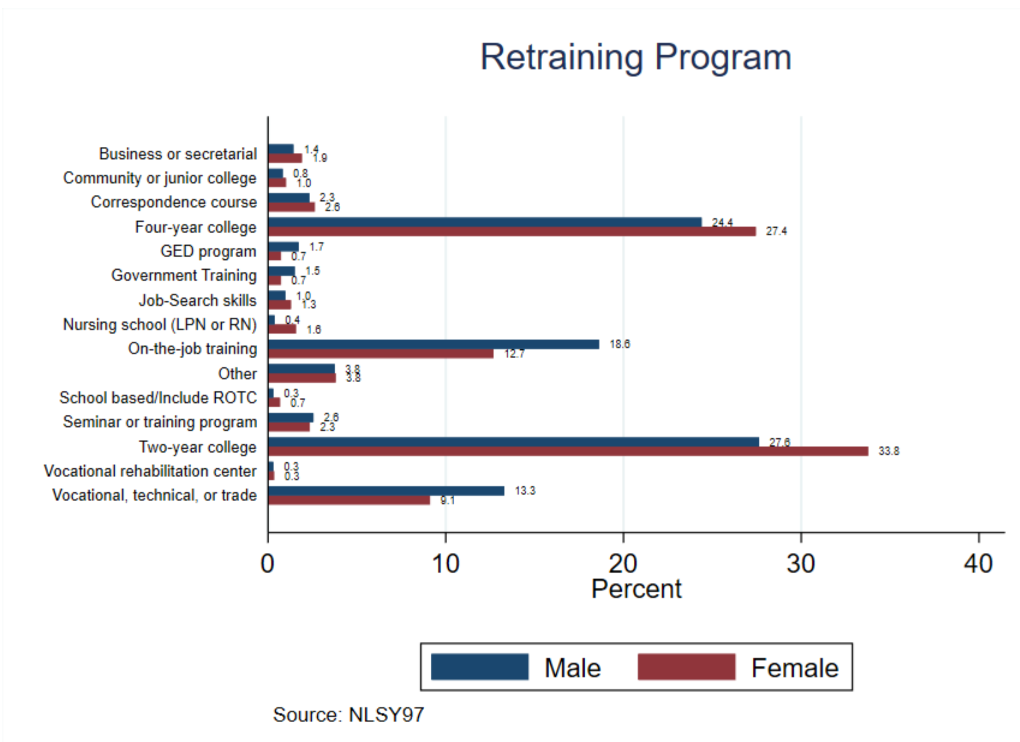
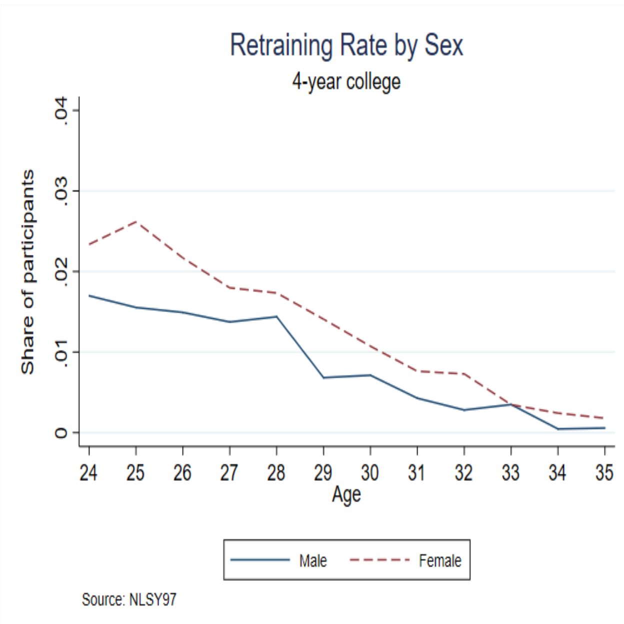


Figure 14: Composition of retraining

Women's higher retraining participation is driven by a college education. Figure 15 and Figure 16 plot retraining rates of the four most popular retraining programs. Women's higher participation rates in two-year and four-year college education are not observed in short-term vocational training and on-the-job training. Gender differences in participation rates are negligible in such programs. Since the purpose of this study is to explain gender disparities in retraining participation, we restrict our attention to a college education.



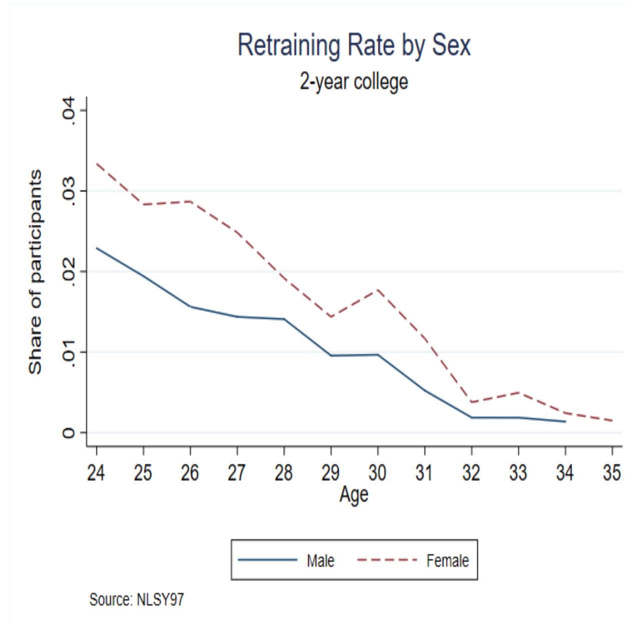


Figure 15: Retraining rate, college education

Table 14 provides summary statistics on the characteristics of retraining participants. Almost 60 percent of participants do not hold a college degree at the time they start retraining. Comparing between men and women, women participants are on average more educated than men. The fraction of participants who hold a Bachelor's degree is significantly higher for women than men. This rules out the possibility that more women put off going to college than men.

Many participants earn while they learn. About 37 percent of them are employed full-time, 23 percent work part-time, and the rest 37 percent are either unemployed or not in the labor force. Women participants are more likely to work part-time than men.

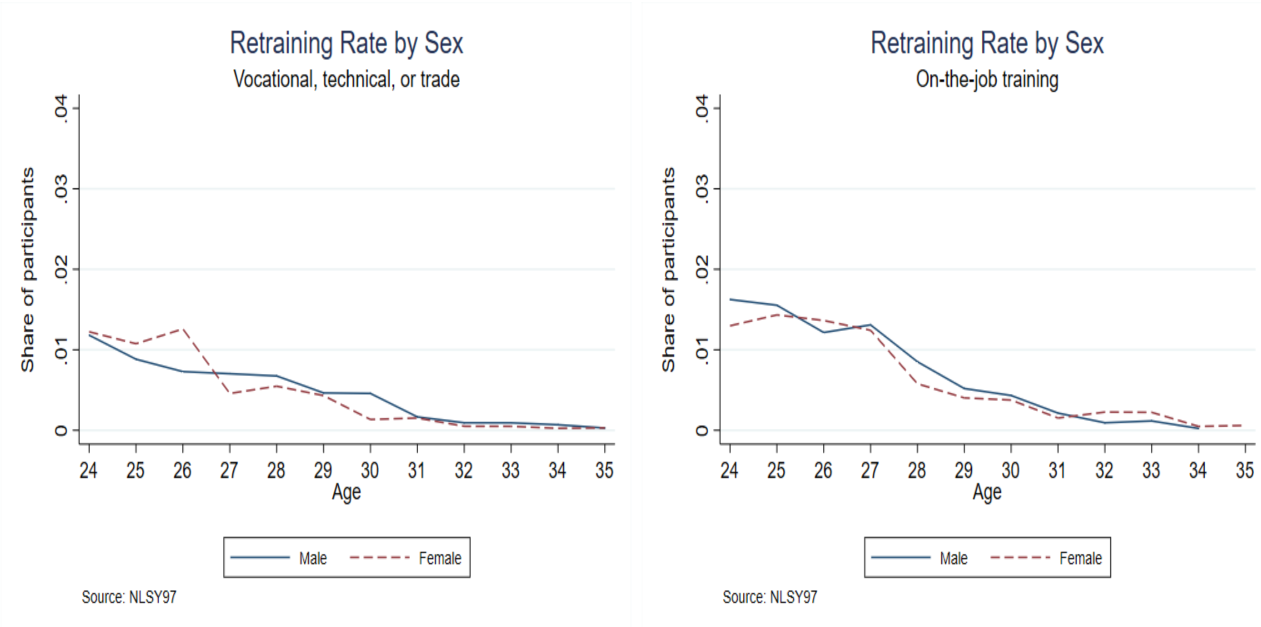


Figure 16: Retraining rate, vocational and on-the-job training

	All	Males	Females	
Age	27.54	27.39	27.63	*
White (%)	45.16	46.24	44.46	
Married (%)	27.91	24.31	30.18	***
Equivalent to HS degree (%)	58.13	63.71	54.13	***
AA degree (%)	19.52	17.73	20.80	
BA degree (%)	20.46	16.91	23.01	**
More than BA degree (%)	1.89	1.65	2.06	
Full-time working (%)	36.68	39.90	34.62	**
Part-time working (%)	23.16	19.01	25.82	***
Not employed (%)	36.95	37.84	36.37	
Observation	1829	718	1111	

*Significant at 10%, **Significant at 5%, ***Significant at 1%

Table 14: Summary statistics, participant characteristics

Table 15 presents the duration, costs, and completion rate of retraining. Participants spend on average about 28 months on retraining. The out-of-pocket expenses per term are about $459. A participant is considered to have completed retraining if the reason she leaves program is because she completed and received a degree and she stayed long enough time at the program. The completion rate is surprisingly low. Only about 24 percent of participants manage to complete the program. Women have a slightly higher completion rate than men, but the difference is not significant.

	All	Males	Females
Duration (month)	28.60	28.41	28.72
Out-of-pocket expense ($)	458.85	443.71	469.08
Completion rate (%)	23.89	22.56	24.75

Table 15: Summary statistics, retraining

2.3 Hypotheses

This section discusses possible explanations for the gender gap in retraining participation. We first test whether social skill differences between men and women can explain women's higher retraining rates. We estimate the return to retraining and see if the return increases with participants' social skills. The results suggest that it is an important mechanism. Next, we consider whether women tend to work in professions where employers are more involved in employee's training. We show suggestive evidence that generous support for workers' continued education in healthcare occupations can explain some of the gender disparities in retraining. Finally, we discuss whether women's second-earner status within households or the disproportionate impact of automation on women plays a role. Neither appears to contribute to gender disparities in retraining participation.

2.3.1 Social Skills

Many studies have addressed the growing importance of social skills in high-paying, college-level occupations. Deming (2017) estimates the return to social skills using the NLSY. He finds that a one standard deviation increase in social skills increases real hourly wages by 10.7 percent. He also shows that workers with a higher level of social skills sort into non-routine and social skill-intensive occupations, which are likely to be high-paying occupations. He explains the popularity of social skills in high-paying occupations as a gain from "task trade". College-level occupations mostly consist of non-routine tasks that require workers to perform a wider set of tasks than lower-skill occupations that are routine task intensive. Workers in college-level occupations can enjoy gains from specialization by focusing on tasks that they have the comparative advantage of and trading with other workers. Higher social skills are valuable in these occupations because they lower the cost of trading. As a result, workers who possess higher social skills have higher productivity, and therefore, higher returns.

Cortes et al. (2018) suggest that the increasing demand for social skills explains women's outpacing performance in the labor market over the past several decades. Under the assumption that women have a comparative advantage at social skill-intensive tasks, they show that high-wage occupations have experienced both an increase in social skill-intensive tasks and an increase in the female share of employment relative to other occupations.

Women's higher social skills could explain the gender disparity in retraining participation as well. Higher returns to social skills in college-level occupations encourage workers with high social skills to receive a college education. If women have on average higher social skills than men, this difference in social skill distribution could lead to higher retraining participation for women.

To examine this hypothesis, in this section, we first compare the distributions of cognitive, non-cognitive, and social skills between men and women in the NLSY97. We then estimate the return to retraining and show that the return increases with participants' social skills.

We create participants' social skill measures following Deming (2017). The NLSY97 provides the Ten-Item Personality Inventory (TIPI). The TIPI test consists of ten pairs of personality traits. The respondents are required to rate how well each pair of traits applies to them, on a scale of 1 to 7. The social skill measure is based on two pairs -Extraverted, enthusiastic and Reserved, quiet- of them. We standardize each variable, take the average across them, and re-standardize the average.

Figure 17 compares the distribution of social skills between men and women in the sample. The figure indicates that women's social skill distribution is more skewed to the left than men's. 60.6 percent of women have social skills higher than the median. The number is 54.1 percent for men. The gender difference in social skills is more pronounced in the lowest social skill group. 26.2 percent of men belong to the lowest social skill group, whereas 20 percent of women have such low social skills. If participants with higher social skills enjoy a higher return to retraining, this difference in social skill distribution will generate the difference in retraining participation.

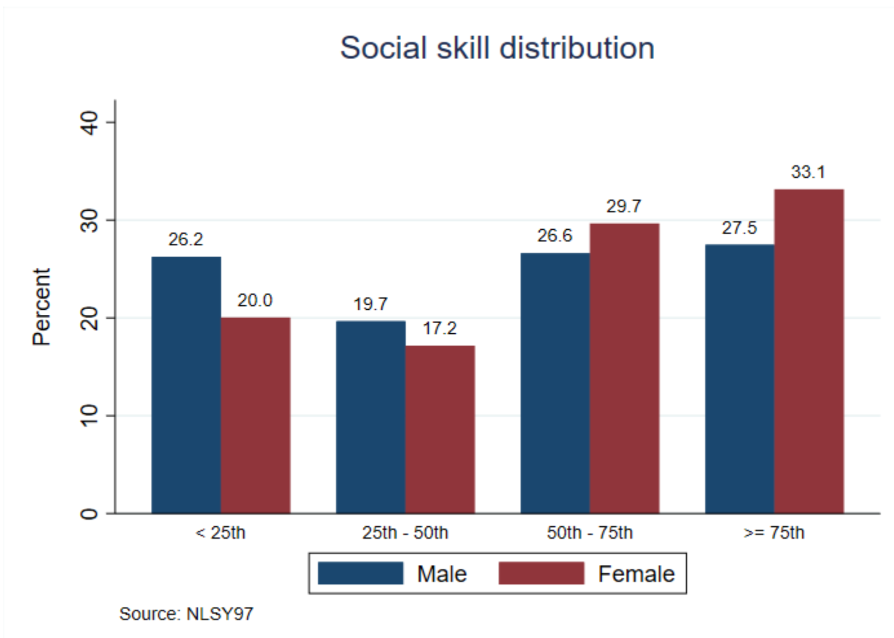


Figure 17: Social skill distribution, by sex

Figure 18 compares the distribution of other skills between men and women. Participants' cognitive skill is proxied by the standardized scores on the Armed Forces Qualifying Test (AFQT). Following Deming (2017), we combine seven traits - organized, conscientiousness, dependability, thoroughness, trustingness, disciplined, and carefulness - to measure participants' non-cognitive skills. Figure 18 indicates that an average woman in the sample is more likely to have higher cognitive and non-cognitive skills than an average man. The differences in cognitive and non-cognitive skills, however, are not as sharp as the differences in social skills.

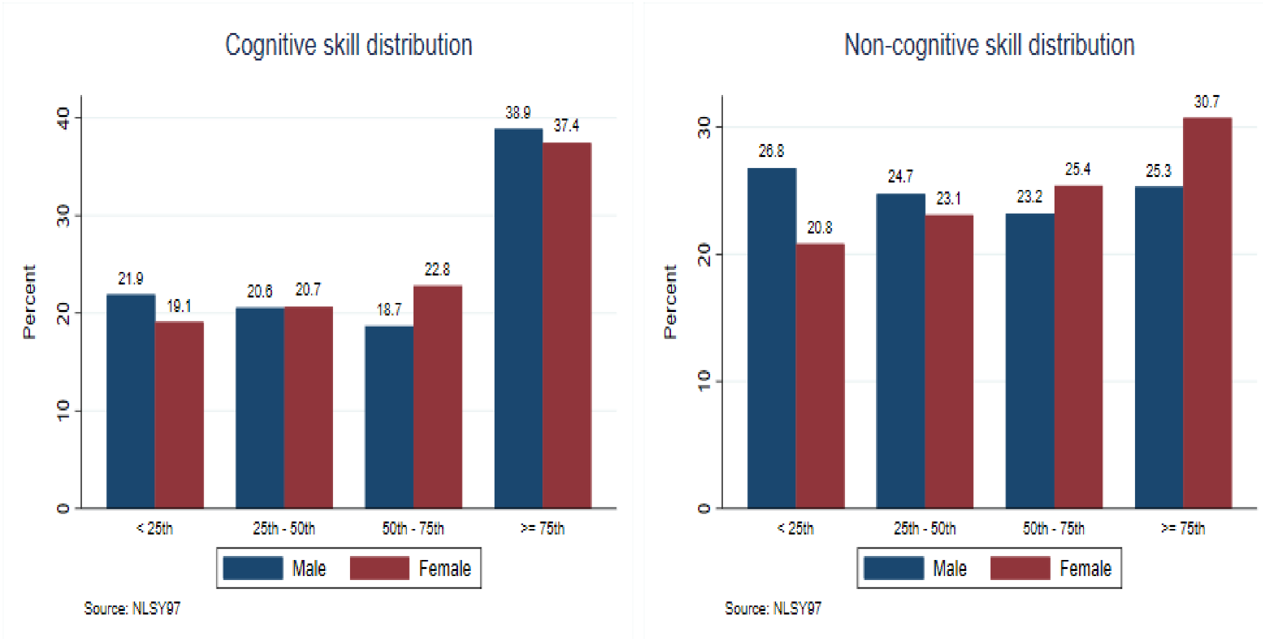


Figure 18: Cognitive and non-cognitive skill distribution, by sex

To observe the relationship between social skills and the return to retraining, we regress log hourly wages on retraining participation and a variety of other covariates:

$$\begin{aligned} ln(wage_{ij}) &= \beta_0 + \beta_1 * RT_{ij} + \beta_2 * RT_{ij} * T_{ij} \\ &+ \beta_3 * RT_{ij} * SS_i + \beta_4 * RT_{ij} * T_{ij} * SS_i + \gamma * X_{ij} + \eta_i + \delta_j + \epsilon_{ij} \quad (2.1) \end{aligned}$$

RT_{ij} identifies participant i's retraining participation. RT_{ij} is one if participant i starts retraining before age j. T_{ij} denotes time since the start of retraining. It is defined as age j minus the age participant i starts retraining. The return to retraining T years after participants start retraining is given as $\beta_1 + \beta_2 * T$. SS_i is participant i's social skills. We include a set of interaction terms, $RT_{ij} * SS_i$ and $RT_{ij} * T_{ij} * SS_i$, to observe how the return to retraining changes as participants' social skills increase.

The results are in Table 16. All specifications include controls for race, gender, skill measures (cognitive, non-cognitive, and social), education level at age 23, occupation, and age and year (indexed by t) fixed effects. The return to retraining is negative up until four years after participants start retraining. This reflects income losses during retraining and the cost of switching careers. Column 1 shows that hourly wages increase by 2.3% every year, and a participant who has one standard deviation higher social skills enjoys a 1.6 % bigger wage increase each year. In column 4, the number becomes slightly lower with other skill measures included but remains statistically significant. Column 2 and column 3 show how the return to retraining changes with cognitive and non-cognitive skills, respectively. We find that neither an increase of cognitive nor non-cognitive skills yields an additional wage gain.

Outcome is Log Hourly Wage	(1)	(2)	(3)	(4)
Retraining	-0.106***	-0.107***	-0.110***	-0.101***
	(0.034)	(0.034)	(0.034)	(0.034)
Retraining * Time	0.023***	0.024***	0.024***	0.022***
	(0.007)	(0.007)	(0.007)	(0.007)
Retraining * Social	-0.038			-0.042
	(0.031)			(0.033)
Retraining * Time * Social	0.016**			0.015**
	(0.006)			(0.007)
Retraining * Cognitive		-0.045		-0.028
		(0.037)		(0.038)
Retraining * Time * Cognitive		0.003		0.001
		(0.008)		(0.008)
Retraining * Noncognitive			0.018	0.016
			(0.031)	(0.033)
Retraining * Time * Noncognitive			0.008	0.002
			(0.007)	(0.007)
Additional Controls	Y	Y	Y	Y
Observations	23,802	23,813	23,802	23,802
Number of individuals	3,345	3,346	3,345	3,345

Note: *Significant at 10%, **Significant at 5%, ***Significant at 1%

Table 16: Return to retraining

Table 16 implies that women's higher retraining participation can be considered as composition effects. Women's retraining rates are higher because there are more women in the upper bracket of the social skill distribution. To see whether this is the case, we modify the regression equation above by including an additional set of interaction terms with the female indicator. The regression equation is given as:

$$
\begin{aligned}
ln(wage_{ij}) &= \beta_0 + \beta_1 * RT_{ij} + \beta_2 * RT_{ij} * T_{ij} \\
&+ \beta_3 * RT_{ij} * SS_i + \beta_4 * RT_{ij} * T_{ij} * SS_i + \beta_5 * RT_{ij} * Female_i + \beta_6 * RT_{ij} * T_{ij} * Female_i \\
&+ \beta_7 * RT_{ij} * SS_i * Female_i + \beta_8 * RT_{ij} * T_{ij} * SS_i * Female_i + \gamma * X_{ij} + \eta_i + \delta_j + \epsilon_{ij} \quad (2.2)
\end{aligned}
$$

β_5 and β_6 show if the return to retraining for women is different from men's. β_7 and β_8 show whether the effects of social skills on the return are different between men and women.

The results are shown in Table 17. The coefficients of female interaction terms are statistically insignificant. It indicates that the return to retraining does not favor a specific gender and that higher returns for participants with higher social skills exist among both men and women. Including cognitive and non-cognitive skills do not change these results.

The only difference between men and women is in the effects of participants' cognitive skills. For women, the return to retraining decreases as participants' cognitive skills increase. We do not observe this among male participants. A male participant who has one standard deviation higher cognitive skills earns 1.9 percent additional wage gain from retraining each year. However, his female counterpart experiences a drop of 1.9 percent instead.

2.3.2 Occupations

Retraining could be more common in a certain group of occupations. Some occupations encourage workers to receive further education by rewarding them with better pay and promotion or sharing some of the education costs.

Nursing, a common female occupation, is one of those occupations that further education is highly encouraged. Although a four-year college degree is not necessary to enter the profession, there has been an increasing effort to raise the proportion of nurses educated at the bachelor's

Outcome is Log Hourly Wage	(1)	(2)	(3)	(4)
Retraining	-0.095*	-0.093*	-0.093*	-0.085*
	(0.049)	(0.050)	(0.050)	(0.051)
Retraining * Time	0.031***	0.028***	0.031***	0.027*
	(0.010)	(0.011)	(0.010)	(0.011)
Female * Retraining	-0.006	-0.012	-0.033	-0.022
	(0.068)	(0.068)	(0.069)	(0.070)
Female * Retraining * Time	-0.018	-0.013	-0.015	-0.014
	(0.015)	(0.015)	(0.015)	(0.015)
Retraining * Social	-0.014			-0.012
	(0.049)			(0.053)
Retraining * Time * Social	0.022**			0.019*
	(0.010)			(0.011)
Female * Retraining * Social	-0.034			-0.038
	(0.064)			(0.067)
Female *Retraining * Time * Social	-0.010			-0.010
	(0.013)			(0.014)
Retraining * Cognitive		-0.075		-0.048
		(0.052)		(0.056)
Retraining * Time * Cognitive		0.019*		0.014
		(0.011)		(0.012)
Female * Retraining * Cognitive		0.076		0.064
		(0.074)		(0.077)
Female * Retraining * Time * Cognitive		-0.038**		-0.036**
		(0.017)		(0.017)
Retraining * Noncognitive			0.011	0.001
			(0.043)	(0.049)
Retraining * Time * Noncognitive			0.008	0.002
			(0.010)	(0.011)
Female * Retraining * Noncognitive			0.040	0.034
			(0.064)	(0.069)
Female * Retraining * Time * Noncognitive			-0.001	0.003
			(0.013)	(0.014)
Additional Controls	Y	Y	Y	Y
Observations	23,802	23,813	23,802	23,802
Number of individuals	3,345	3,346	3,345	3,345

Note: *Significant at 10%, **Significant at 5%, ***Significant at 1%

Table 17: Return to retraining, by sex

level. In 2010, the Institute of Medicine (IOM) recommended healthcare organizations increase the share of BSN-prepared nurses to 80 percent by the year 2020. In 2017, New York State passed the BSN in 10 law, under which registered nurses (RNs) are required to obtain a Bachelor of Science in Nursing (BSN) within a decade of receiving their RN license.

In response to a high demand for quality nurses, many local hospitals offer financial assistance such as tuition reimbursement to have their nurses work toward a BSN. There are government programs in place as well. Nurse Corps Loan Repayment Program pays up to 85% of unpaid nursing education debt for licensed registered nurse, advanced practice registered nurse, and nurse faculty member in exchange for working at a Critical Shortage Facility or an eligible school of nursing for at least two years.

Education, another female dominant profession, also has bespoke government-sponsored financial aid programs. TEACH Grant, Teacher Loan Forgiveness Program, and Teacher Loan Cancellation Program provide current or future teachers financial assistance in exchange for teaching in a low-income school for a certain period of time. Since Health and Education occupations are traditionally female-dominated, relatively generous support from such occupations could encourage women seeking a second-career to consider pursuing a college education.

Figure 19 shows the current or the most recent occupations participants hold before they start retraining. A large fraction of both men and women participants work or worked in office and administrative support occupations and sales occupations, which are typical routine occupations where employment has been declining. The share of food preparation and serving occupations is also high in both groups.

Occupations that show the most profound gender differences are healthcare and education related occupations. Healthcare related occupations are the second most popular occupations among women participants. About 16 percent of women participants have worked healthcare practitioner and technical occupations or healthcare support occupations. Education, Training, and Library occupations also make up a big portion of women. About 7.4 percent of women participants have held such occupations. In contrast, only about 5.6 percent of men participants have worked in healthcare and education related occupations combined. Among men, the fraction of routine manual occupations is high (28 percent).

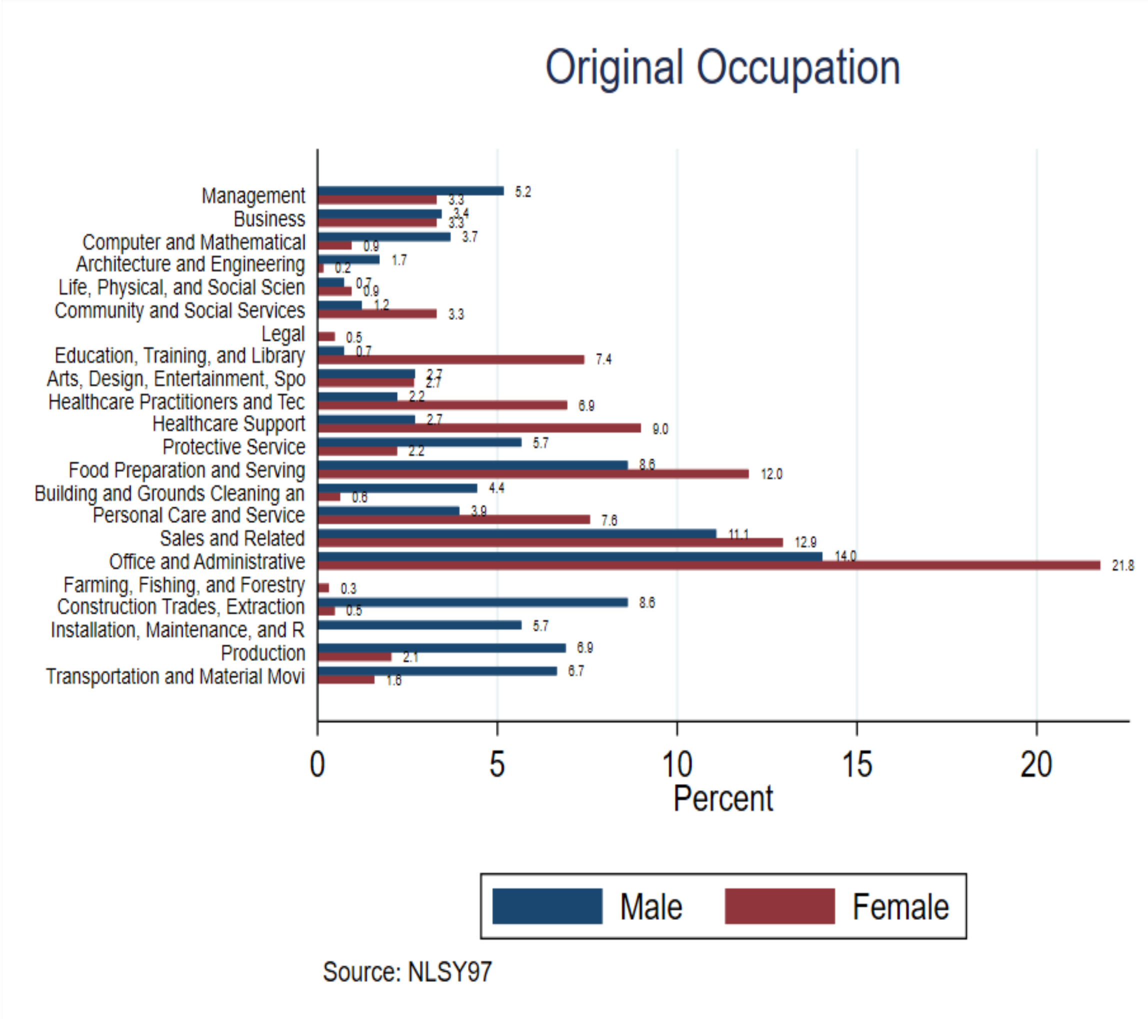


Figure 19: Original occupations of retraining participants

Figure 20 presents majors participants choose in college. For men, most popular majors include business, management, and marketing related, computer and information sciences, and health related programs. For women, health related programs are the most popular by a large margin. Business related programs are popular among women as well as men. Education is quite popular among women, but only a few men choose it. Computer sciences is the opposite. It is one of the most popular subjects among men, but only a little over 1 percent of women choose it as a major.

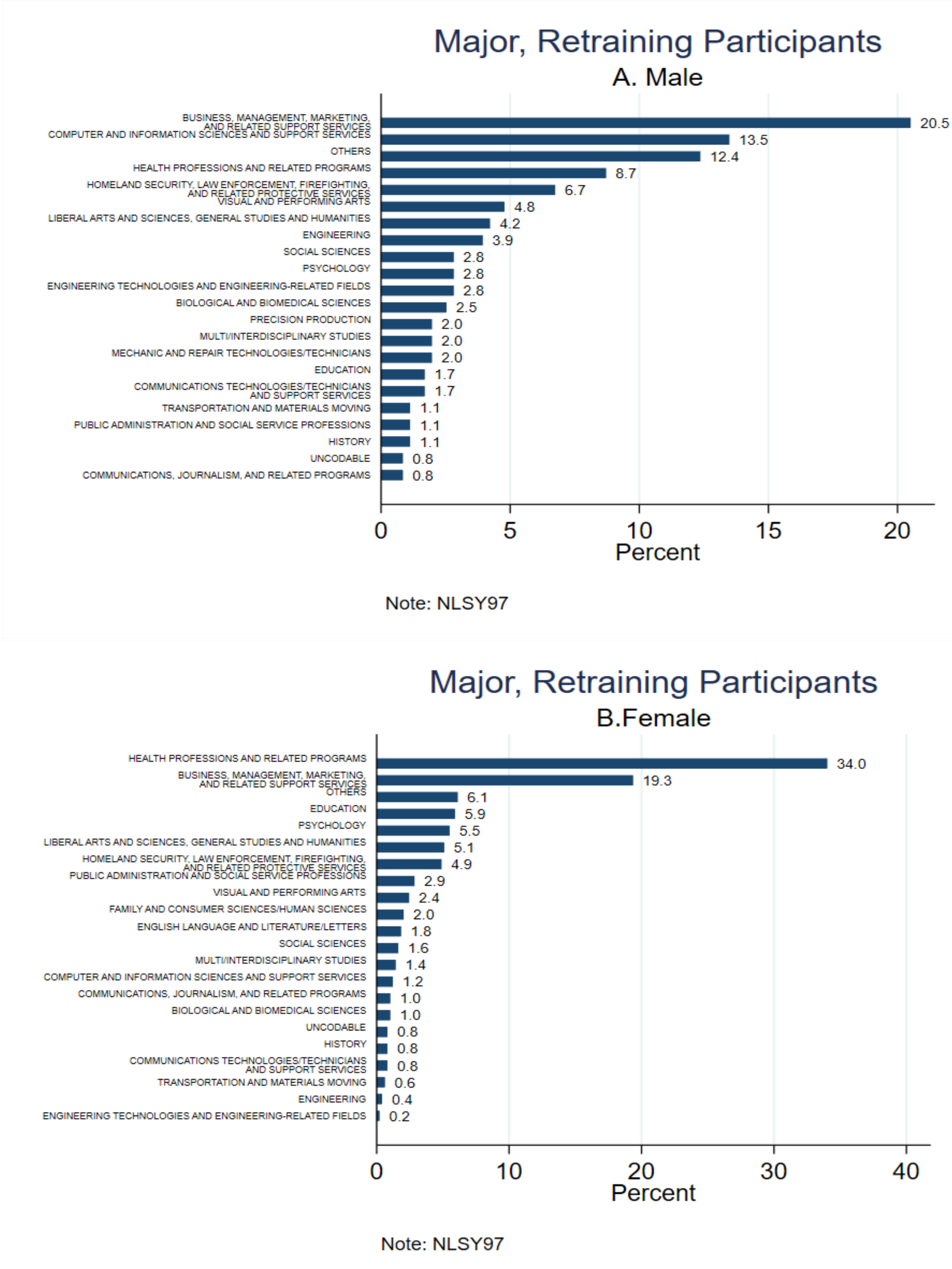


Figure 20: Majors of participants

We observe a correlation between occupation and the major they choose in college among female participants. 67 percent of those who have had health related occupations major health professions and related programs. 25 percent of those who worked in the education profession opt into education related programs. However, we do not see such a correlation among men. It indicates that generous employer support for workers' continued education in professions in which about a quarter of working-age women work is contributing to women's higher participation in retraining.

2.3.3 Marital Status

Workers who have working spouses are in a better position to pursue a different career because they do not have to worry as much about making a living as singles do. Table 14 shows that the share of married among participants is significantly higher for women than men. Within those who are married, spouses' annual income is almost twice as high for women participants. Table 18 compares spouse wages between participants and non-participants. Participants who are married have about 33 percent higher spouse wages than non-participants. All of the above raises the possibility that women's higher retraining rates could be because of the higher fraction of secondary earners among them.

	Participants	Non-participants	
All	16830.67	12613.96	***
Males	13597.2	9334.14	***
Females	19293.08	16381.93	**

Note: **Significant at 5%, ***Significant at 1%

Table 18: Comparison of spouse wages

Although spouse wages appear to be an important predictor in one's retraining decision, it does not fully explain the gender gap in retraining. Figure 21 plots retraining rates by marital status. The gender gap in retraining exists among both singles and married workers. Differences in spouse wages may explain some of the gender disparities among the married.

However, they do not explain the gender gap that exists among singles, who make up a larger portion of participants.

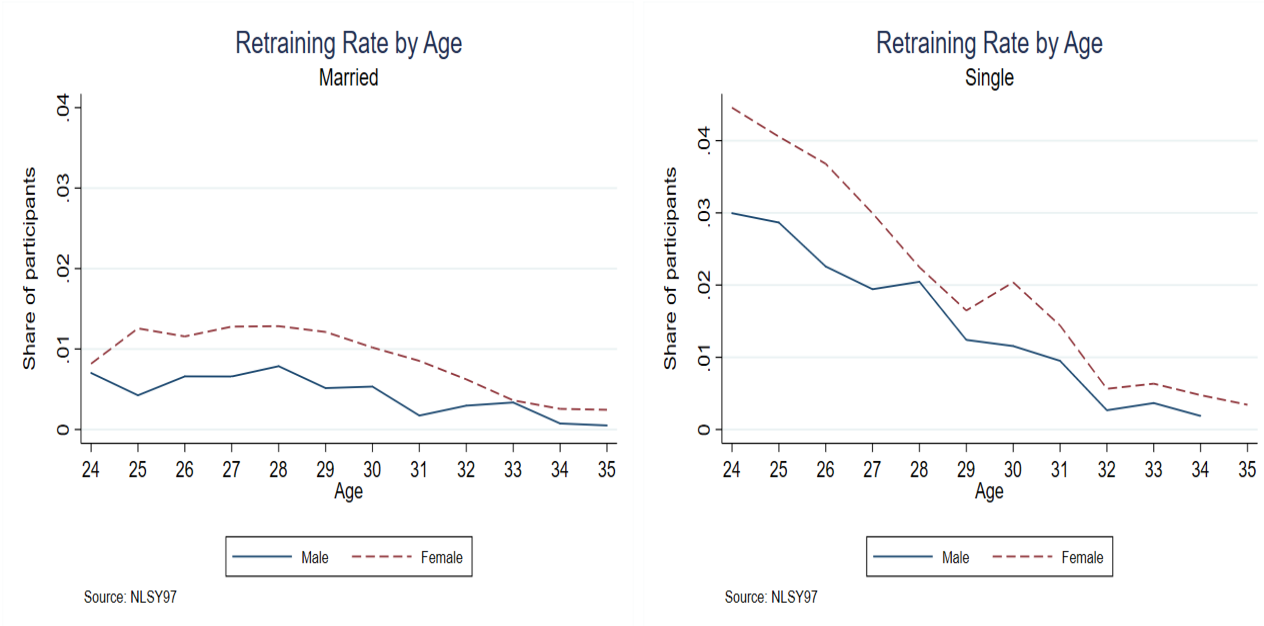


Figure 21: Retraining rate, by marital status

2.3.4 Non-college Job Opportunities

Workers would not bother to go to college if they have plenty of career options they can consider without a college education. This could matter more to workers who consider going back to school in the middle of a career if many of them consider a career change because the prospects in their current career are not promising. Kim (2020) shows that decreasing job opportunities in high-school level occupations is the most important factor that has contributed to the rise in retraining. The contribution is even bigger than increasing college wage premium.

If employment opportunities for low-skill workers are more abundant for men, that could contribute to their relative reluctance to retrain. Chuan (2017) makes a similar argument. She shows that women's decreasing non-college employment opportunities due to the automation of office and administrative support occupations have increased women's college enrollment. She observes a widening gender gap in college enrollment in the local labor market with a higher fraction of routine-intensive occupations.

In this section, we address the possibility that low-skill women have been hit harder by automation than low-skill men. They choose to retrain themselves to compensate for their declined job opportunities. We use job transition rates as the measures of workers' job opportunities. Job finding rates show how easy it is for workers to find a job, and job separation rates show how stable workers' current jobs are. If there are more work opportunities for low-skill men than women, they will observe higher job finding rates and lower job separation rates.

Table 19 and Table 20 present evidence against Chuan (2017). Monthly job finding rates for low-skill men in the NLSY97 are about 13.1 percent. It is only slightly higher than women's job finding rates of 12.4 percent. We do not observe significant gender differences in job separation rates either. Overall, we do not find evidence that men have more abundant non-college job opportunities than women.

	Males	Females
NRCG	1.1%	2.4%
RCG	2.9%	5.6%
RMN	6.4%	1.4%
NRMN	2.7%	3.0%
All	13.1%	12.4%

Table 19: Job finding rates, workers with no college education

	Males	Females
NRCG	0.1%	0.2%
RCG	0.3%	0.5%
RMN	0.6%	0.1%
NRMN	0.2%	0.3%
All	1.2%	1.2%

Table 20: Job separation rates, workers with no college education

2.4 Conclusion

In this paper, we address possible explanations of gender disparities in retraining participation in the U.S. We discuss the role of social skills, occupations, marital status, and non-college job opportunities.

Our main focus is the contribution of social skills. Workers' social skills are valued more in high-paying, college-level occupations where collaborative work among co-workers is more important. The higher demand for social skills in college-level occupations motivates workers with high social skills to go to college. If there are gender differences in social skills, it will result in differences in retraining participation. Using the NLSY97, we show that women have on average higher social skills than men and that the return to retraining is bigger for participants who possess higher social skills. This evidence supports the hypothesis that gender disparities in retraining participation come from the differences in social skills.

We also show evidence that female occupations are more supportive in terms of workers' education than male occupations. For example, healthcare occupations encourage their workers to work toward higher degrees by providing various tuition reimbursement programs, contributing women's higher retraining rates. Spouse's wages affect retraining participation. Although women are more likely to be second earners within households, it does not explain the gender gap that exists among singles. We do not find evidence that low-skill women are hit harder by automation than low-skill men.

3.0 The Static and Dynamic Effects of Collaboration[1]

3.1 Introduction

Collaboration among researchers in economics has been substantially increasing. As shown in Figure 22, the share of solo-authored papers in the field of Economics and Business has been persistently decreasing. The share of double-authored papers started to decrease from the early 2000s. In contrast, the share of papers written by more than two authors has been continuously increasing. In the year of 2018, three-authored papers comprise the largest share among the papers published in the top 100 Economics and Business journals.

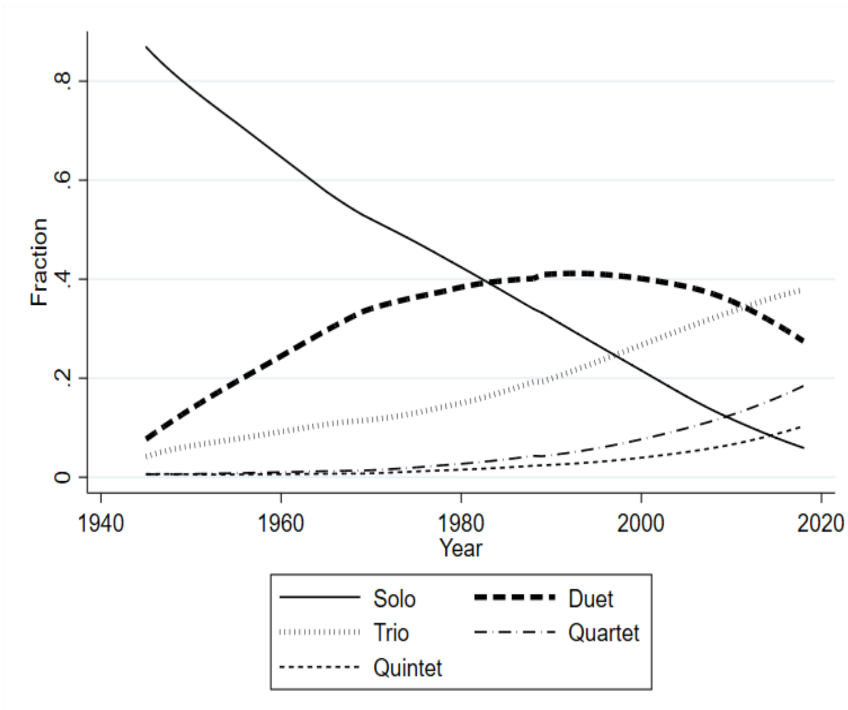


Figure 22: Co-authorship trend over time

Does academic collaboration always yield a better outcome than solo work? How does it affect participants' research productivity? It is important to answer these questions as collab-

[1]This chapter is coauthored with Douglas Hanley and Sewon Hur.

oration becomes more and more common in academia. There have been many studies that try to examine the effect academic collaboration has on research productivity, but there is no full agreement. Laband and Tollison (2000), Wuchty et al. (2007), Chung et al. (2009), Azoulay et al. (2010), and Ductor (2015) show collaboration enhances research productivity while Medoff (2003) and Bozeman and Corley (2004) suggest there is no effect. Hollis (2001) even finds negative effects. In this paper, we suggest a new approach to understand the static and dynamic effects of academic collaboration on research productivity.

What distinguishes our study from the existing literature is that we specify a functional relationship between collaboration and productivity. In our framework, a researcher's human capital is a function of his publication history and innate ability. When a group of researchers decides to collaborate, their human capital is combined by the CES production technology and produces a research outcome. The elasticity of substitution in the CES production function measures the degree of complementarities between any two researchers. We estimate the researchers' human capital function and research outcome production function using the information on published papers from 1970 to 2018 in the field of Economics and Business.

Our point estimate of the elasticity of substitution between researchers is around 0.96, suggesting that researchers are imperfect complements. Using the estimated functions and the data on published papers, we document a set of stylized facts about collaboration. We find that academia consists of a large number of researchers with low human capital and only a few researchers with high human capital. Collaboration mostly takes place among equally productive researchers. Researchers' human capital is closely related to the quantity and quality of co-authorship; researchers with higher human capital have more collaboration opportunities and tend to collaborate with more highly productive researchers.

To understand the effects of collaboration on researchers' productivity, we simulate the human capital growth of the median researcher under different collaboration scenarios. Comparing a scenario of solo work to a scenario of collaboration, we find that collaborating with an equally productive coauthor generates around 40% of gain in human capital. This 'teamwork premium' persists over time. We show that the link between researchers' human capital and the quantity and quality of collaboration opportunities plays an important role in explaining the persistent effects of collaboration. The rise in human capital from the initial collaboration brings the researcher more collaboration opportunities with more highly productive researchers, which translate into even bigger human capital growth. In the counterfactual analysis where we ignore the link, we show that the effects of collaboration on the researcher's human capital diminish quickly over time.

The effects of collaboration vary by researchers' human capital, coauthors' human capital, and the number of coauthors. We assign the given researcher a set of different coauthors and see the resulting effects on human capital. We find that conditional on having an equally productive coauthor, the immediate gain from collaboration is bigger for low-productivity researchers. However, in the long run, the benefit of collaboration is bigger for highly productive researchers. We also show that the teamwork premium increases with the coauthors' human capital and decreases with the number of coauthors.

This study is related to the literature on the relationship between academic collaboration and research productivity. The contribution of this paper to this literature is threefold. First, we specify a functional relationship between collaboration and research productivity, whereas other papers simply assume linearity. We measure the degree of complementarities between researchers by estimating the elasticity of substitution between researchers. Second, we examine the dynamic effects of collaboration. We show that the effects of collaboration are persistent over time due to the interaction between human capital and future collaboration opportunities. Third, we study the effects of collaboration between asymmetric researchers. Our framework allows us to experiment with various types of collaboration by assigning a given researcher a set of coauthors with different characteristics.

This study is also related to the literature estimating the elasticity of substitution between workers. A large set of papers estimate the elasticity of substitution between skilled and unskilled workers (Fallon and Layard, 1975; Katz and Murphy, 1992; Angrist, 1995; Card and Lemieux, 2001; Ciccone and Peri, 2005), between natives and immigrants (Card, 2001; Borjas, 2003; Peri and Sparber, 2009; Borjas et al., 2008; Barone and Mocetti, 2011; Ottaviano and Peri, 2012), or between males and females (Acemoglu et al., 2004; De Giorgi et al., 2013). Unlike other papers focus on complementarities between different types of workers, we examine it between more homogeneous workers -highly educated academics- whose work inherently requires a high level of collaboration. To our knowledge, this is the first attempt to estimate the elasticity of substitution between academics.

An outline of the paper follows. Section 2 presents the model. Section 3 describes the data. Section 4 describes the estimation methodology and presents the results. Section 5 explores the relationship between collaboration and research productivity. Section 6 provides the conclusion.

3.2 Model

3.2.1 Researchers' Human Capital

Researchers' human capital evolves over time following the law of motion below:

$$H_{rt} = X_{rt} + (1-\delta)H_{r,t-1} + \nu_r \tag{3.1}$$

H_{rt} denotes researcher r's human capital in time t. It consists of newly-accumulated human capital X_{rt}, human capital from the previous period, $H_{r,t-1}$, and the researcher's innate research ability, ν_r. δ denotes the human capital depreciation rate.

X_{rt} is measured as the quality adjusted publications in time t. It consists of the quantity and quality of publications, taking the form of Cobb-Douglas production function. X_{rt} is given as:

$$X_{rt} = P_{rt}^{\alpha_1} Q_{rt}^{\alpha_2} \tag{3.2}$$

where P_{rt} is the number of papers researcher r publishes in time t and Q_{rt} is the average quality of those papers. α_1 and α_2 are the output elasticities of the quality and quantity of the publications, respectively. Q_{rt} is given as:

$$Q_{rt} = \frac{\sum_{p \in P_{rt}} \theta_{rp} q_{pt}}{P_{rt}} \tag{3.3}$$

where q_{pt} denotes the quality of individual publication p in time t, and θ_{rp} denotes researcher

r's contribution to p. We assume $\theta_{rp} = \frac{1}{\sqrt{A_p}}$[2].

Put together, researcher r's human capital in time t is a function of his publication history and innate ability. H_{rt} is given as:

$$H_{rt} = f(P_{rt}, Q_{rt}, P_{r,t-1}, Q_{r,t-1}, \cdots, P_{r,t^*(r)}, Q_{r,t^*(r)}; \alpha_1, \alpha_2, \delta) + \nu_r \tag{3.4}$$

where $r, t^*(r)$ is the time that researcher r first appears in academia.

3.2.2 Research Output Production

A group of researchers works on the same research project as a team. Each member's human capital accumulated up until period t_p, the time publication p is created, is combined by the CES production technology. Each team produces one publication. The production function is therefore given by:

$$q_p = A_p^{\beta} \left[\sum_{r \in R} \frac{1}{A_p} \left(H_{rt_p-1} \right)^{\rho} \right]^{\frac{1}{\rho}} + \epsilon_p, \quad \rho \in (-\infty, 1), \quad \epsilon_p \sim N(0, \sigma_{\epsilon}^2) \tag{3.5}$$

where q_p is the quality of publication p, and H_{rt_p-1} is the human capital of researcher r in tim $t_p - 1$. A_p is the number of authors of publication p. β measures the effects of the size of the team on the quality of the publication. ρ is the substitution parameter. The elasticity of substitution between any two researchers is defined as:

$$\sigma = \frac{1}{1-\rho} \tag{3.6}$$

It measures the degree of complementarities between any two researchers. Researchers are gross substitutes if $\sigma > 1$, and gross complements if $\sigma < 1$. ϵ_p is the error term. We assume it follows the standard normal distribution.

[2]This is a common way for schools to calculate the contribution of a researcher to a co-authored paper when they decide on the researcher's salary (Hamermesh, 2013).

3.3 Data and Variables

In this section, we discuss the data and the construction of the variables. The main data set we use is obtained from Web of Science. It contains detailed information on papers published between 1970 and 2018 in the top 100 Economics and Business journals. The journal ranking is obtained from Scimago journal and country rank[3]. The data set provides papers' titles, author' names, authors' affiliations, year of publication, name of journals, length, and number of citations.

3.3.1 Paper Quality

We use both citation and journal information to measure the quality of the paper. The quality of paper q_p is given as:

$$q_p = \frac{TC_p \times SJR_{pt_p}}{PG_p} \tag{3.7}$$

TC_p is the annual average of total citations. It is defined as the total number of citations the paper has received as of the year 2018 devided by the age of the paper. SJR_{pt_p} is a widely used measure for journal prestige. It is calculated as the average number of weighted citations in the selected year divided by the number of documents published in the journal in the three previous years. PG_p is the length of the manuscript. Since longer papers receive more citations, we include the number of pages of the manuscript in the denominator.

3.3.2 Ability

Since researchers' innate ability ν_r is not observable, we use the information on researchers' first affiliations to approximate it. Researchers' research ability is evaluated officially for the first time in the job market. Given that a researcher's job market result is the combination of the quality of his job market paper, the school that he receives his degree from, and the advisors' subjective opinion on his ability, using the information on his first affiliation as a

[3] A list of the journals can be found in Table 1

proxy for his research ability seems reasonable. We measure the quality of an institution in a given year as the three-year average of the quality of the papers that its researchers produce.

3.3.3 Affiliations

Since we use the first affiliation of a researcher as the proxy for his ability, it is crucial to identify each researcher's primary affiliation. However, unfortunately, we do not always observe the primary affiliation of each author. For some cases, we only have a list of authors' names and a list of the affiliations, but not the exact matching between them. To solve this problem, we calculate π_{irt}, the probability that researcher r works for institution i in period t. For each publication $p \in P_{rt}$ of researcher r in period t, we define $\pi_{iprt} = 1$ if the institution is uniquely identified and $\pi_{iprt} = \frac{1}{I_{prt}}$ if the institution is not uniquely identified where I_{prt} is the number of institutions listed in publication p. $\pi_{iprt} = 1$ in the case of single authors, single listed institutions, reprint authors, and papers published after 2007. π_{irt} is given as:

$$\pi_{irt} = \frac{\sum_{\tau=t-3}^{t+3} \sum_{p \in P_{r\tau}} \pi_{ipr\tau} w(\tau, t)}{\sum_{\tau=t-3}^{t+3} \sum_{p \in P_{r\tau}} w(\tau, t)} \tag{3.8}$$

where $w(\tau, t)$ are weights centered around $\tau = t$. π_{irt} is well-defined if r has at least one publication in a 7-year window.

Another problem with the data set is that, for the papers published prior to 2008, we do not observe the authors' full names. Only the last names and the initials of the first names are listed. It is problematic since we can't tell apart the researchers who share the same last name and the initial of the first name. It is more pronounced among Asian authors since there is less variation in Asian last names. To avoid potential bias it can cause, we start our analysis with the papers published after 2007. This way, we can identify each researcher's full name and primary affiliation for sure. A downside of restricting the sample to the papers published after 2007 is that we do not observe first affiliations for those who enter academia prior to 2008. We use their affiliation information in 2008 instead. We further restrict the sample to the papers with five or fewer authors. Less than 1% of the papers have more than 5 authors. The final data set consists of $52,027$ papers and $62,165$ researchers. Table 21 presents summary statistics of the data. An average researcher in the data produces one paper per year. He collaborates with other researchers for most of the papers. He has 2 coauthors per year. An average paper in the data is 6 years old, receives 23 citations, has a SJR measure of 4, and is written by 2.4 authors.

	Mean	SD	Min	Max
A. authors (n. 62,165)				
Number of papers	1.16	0.33	1	6.45
Average paper quality	0.53	0.81	0	58.13
Share of co-authored papers (%)	94.47	17.85	0	100
Number of coauthors	2.07	1.02	0	14
Number of coauthors per paper	1.78	0.78	0	4
B. papers (n. 51,512)				
Age	5.62	3.11	1	11
Number of citations	23.15	46.82	1	2461
Journal quality (SJR)	3.99	3.8	0.21	22.9
Pages	20.28	10.51	1	118
Number of authors	2.43	0.91	1	5

For panel A, all variables are the yearly average.
The average paper quality is calculated following equation (7).
The age of papers is calculated as 2018-the year published+1.
SJR is obtained from Scimago Journal & Country Rank, the rest from Web of Science.

Table 21: Summary statistics

3.4 Estimation

3.4.1 Empirical Strategy

In this section, we discuss the estimation strategy of the model. The right hand side of our regression equation consists of two non-linear equations, one of them is nested inside of the other. Neither equation takes a particularly complex form. Once nested, however, the estimation process can get challenging. To avoid unnecessary complexity, we develop a method that allows us to estimate each equation separately.

The estimation of the model is a two-stage process. In the first stage, we estimate α_1, α_2, and δ. In this stage, we restrict the sample to the solo-authored papers. The estimation equation (5) then reduces to the following equation:

$$\begin{aligned} q_p &= H_{rt_p-1} + \epsilon_p \\ &= X_{rt_p-1} + (1-\delta)X_{rt_p-2} + (1-\delta)^2 X_{rt_p-3} + \cdots (1-\delta)^t X_{r0} + \nu_r + \epsilon_p \\ &= P^{\alpha_1}_{rt_p-1} Q^{\alpha_2}_{rt_p-1} + (1-\delta) P^{\alpha_1}_{rt_p-2} Q^{\alpha_2}_{rt_p-2} + \cdots + (1-\delta)^t P^{\alpha_1}_{r0} Q^{\alpha_2}_{r0} + \nu_r + \epsilon_p \end{aligned} \tag{3.9}$$

We apply nonlinear least square estimation to estimate equation (9).

With equation (1) and estimated parameters α_1, α_2, and δ, we calculate each researcher's human capital, H_{rt}. In the second stage, we estimate β and σ. To make the estimation process simpler, we obtain a linear approximation of the CES production function around $\rho = 0$ following Kmenta (1967). We first take logarithm over equation. The log-transformation of the equation is given as:

$$\ln q_p = \beta \ln A_p + \frac{1}{\rho} \ln \left[\sum_r \frac{1}{A_p} (H_{rt_p-1})^\rho \right] \tag{3.10}$$

The second degree Taylor Polynomial for $\ln \left[\sum_r \frac{1}{A_p} (H_{rt_p-1})^\rho \right]$ is given as:

$$\ln \sum_r \frac{1}{A_p} (H_{rt_p-1})^\rho \approx \rho \frac{1}{A_p} \sum_r \ln H_{rt_p-1} + \frac{\rho^2}{2} \frac{1}{(A_p)^2} \left[\sum_r (\ln H_{rt_p-1})^2 - (\sum_r \ln H_{rt_p-1})^2 \right] \tag{3.11}$$

We replace $\ln \left[\sum_r \frac{1}{A_p} (H_{rt_p-1})^\rho \right]$ in equation (10) with its quadratic approximation shown in equation (11). Then the final regression equation is as follows:

$$\ln q_p - \frac{1}{A_p} \sum_r \ln H_{rt_p-1} = b_1 \ln A_p + b_2 \sum_i \sum_j \ln H_{it_p-1} \ln H_{jt_p-1} \tag{3.12}$$

where $b_1 = \beta$ and $b_2 = \frac{\rho}{2}$.

3.4.2 Result: Human Capital Function

Table 22 reports the estimation results from the first stage. The estimates are all statistically significant. The results suggest that human capital responds more sensitively to the quality than the quantity of the paper. A 1% increase of the average paper quality is associated with 0.462% increase in human capital while a 1% increase of the paper quantity yields 0.129% increase in human capital. The depreciation rate is estimated to be around 0.641.

	Coef.	Std. Err.	
α_1	0.129	0.074	*
α_2	0.462	0.030	***
δ	0.641	0.037	***
Obs	6,660		

Time fixed effects are included.
*significant at 10%
**significant at 5%
***significant at 1%

Table 22: Human capital function, mixed-effects ML nonlinear regression

With the estimated values of α_1, α_2, and δ, we calculate each researcher's human capital over time following equation (1) and (2). Figure 23 presents the distributions of researchers' human capital. The distribution of human capital is skewed to the right, with a large number of researchers with human capital close to zero. The distribution of log human capital is close to the normal distribution. Figure 24 displays the cumulative distribution of researchers' human capital. It also shows that academia consists of a few researchers with high human capital and a large number of researchers with low human capital. This finding is similar to what Conley and Onder (2014) find in their analysis on the productivity of new economics Ph.D.s. They find that the majority of the economics PhD graduates fail to produce a creditable number of publications by their sixth year after graduation[4]. Our results show that we can observe the same pattern in human capital of a larger set of economists.

[4]The number of AER-equivalent papers of the median at year six is below 0.1 in all cases and is in fact zero in most(Conley and Onder, 2014).

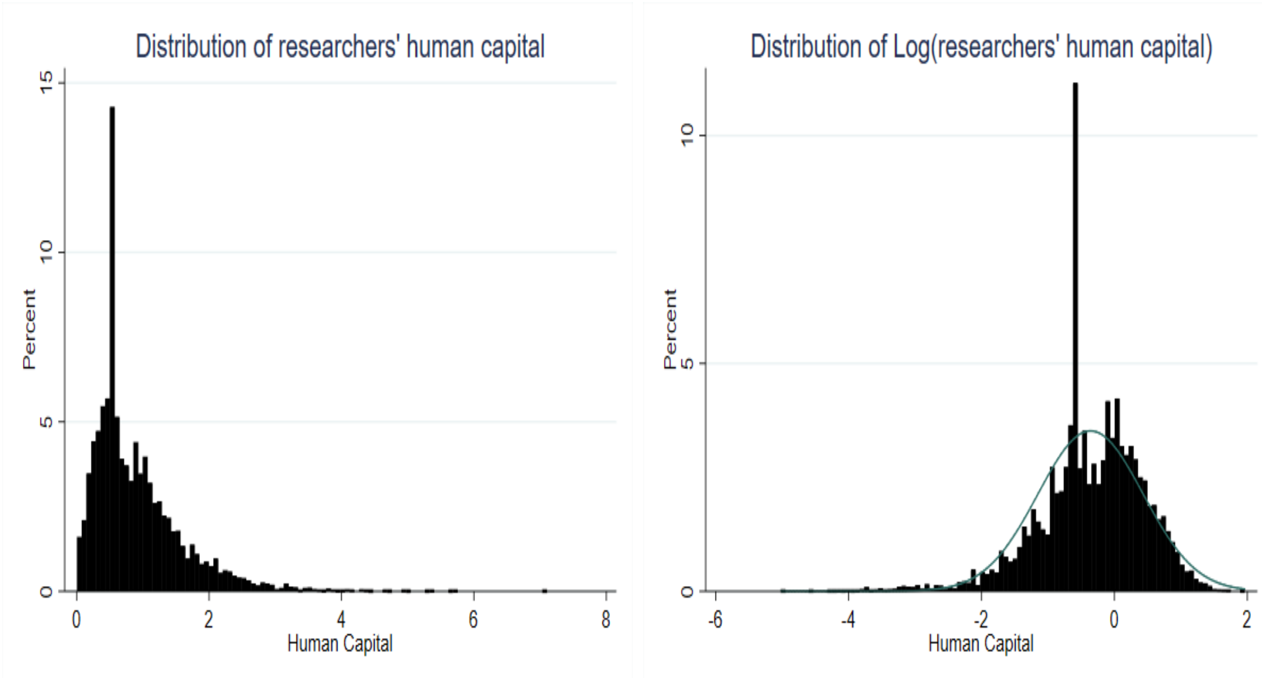


Figure 23: Distribution of human capital of researchers

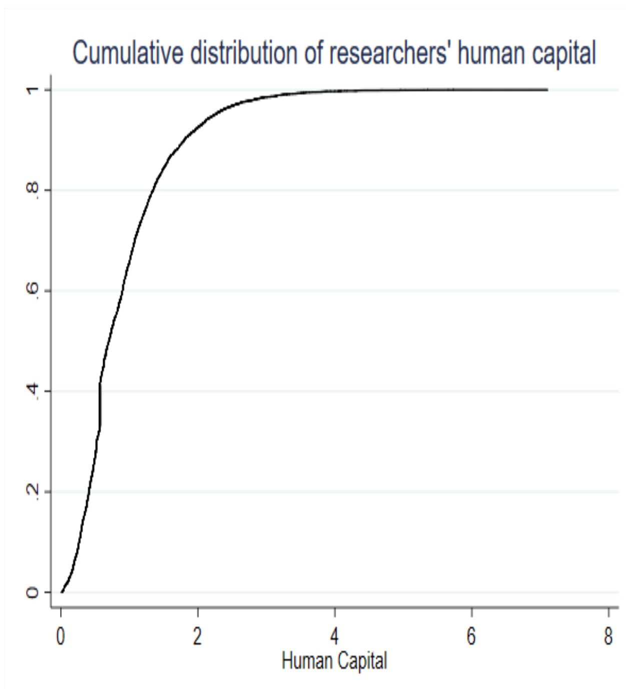


Figure 24: Cumulative distribution of human capital of researchers

We use researchers' human capital to understand how co-authorship is formed. We compare human capital of coauthors of each paper. Figure 25 displays the distribution of papers according to the average absolute deviation of human capital among coauthors. The distribution is rightly skewed, showing that human capital differences among authors are small for most papers. It is more pronounced for the papers with fewer authors. We find that the average absolute deviation of human capital among authors is within one standard deviation in 92% of the cases. These results imply that collaboration mostly takes place among similarly productive researchers.

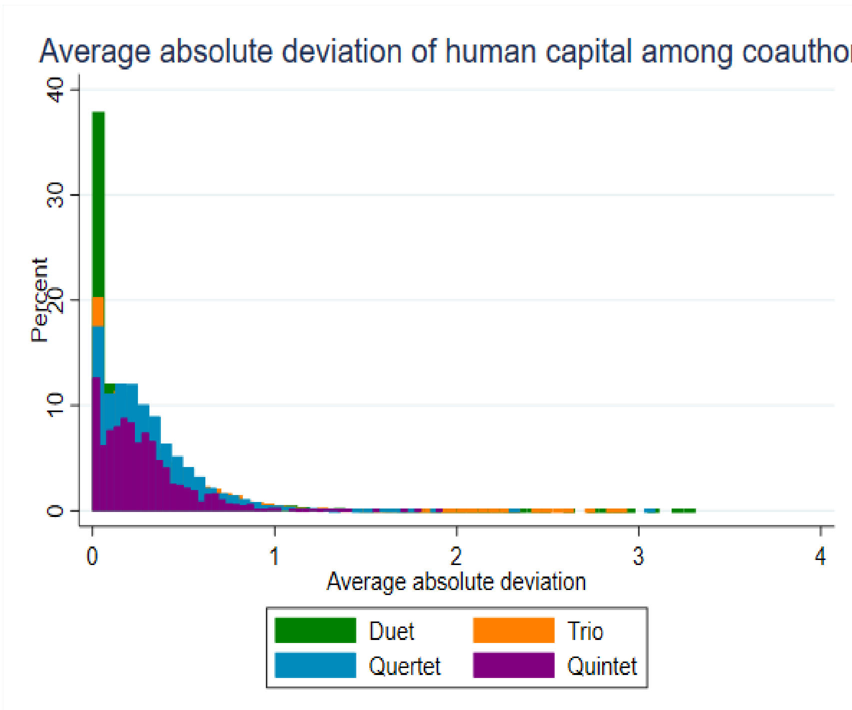


Figure 25: Distribution of papers over the average absolute deviation of human capital

Now we turn our interest to the relationship between researchers' human capital and their collaboration opportunities. How many collaboration opportunities a researcher can have largely depends on his human capital. Researchers choose whom to work with. It is not hard to imagine that highly productive researchers will receive more offers than low-productive researchers. Human capital does not just affect the amount of co-authorship. It also affects the quality of the potential coauthors a researcher can have. Highly productive researchers will be willing and able to work with other highly productive researchers than low productive researchers will be.

To examine the effects of a researcher's human capital on the quantity and quality of his coauthors, we regress a set of variables on human capital of the researchers. The set of dependent variables includes (1) the number of solo papers, (2) the number of co-authored papers, (3) the number of coauthors, (4) the number of coauthors per paper, and (5) the average coauthor human capital. Each regression also includes year fixed effects to control for time-varying factors that can affect the dependent variables.

The estimation results are summarized in Table 23. Column 1 through 4 in Table 23 present the effects of human capital on the quantity aspect of co-authorship. An increase in human capital increases the number of solo papers, co-authored papers, coauthors, and coauthors per paper. The effects are statistically significant but very small. Column 5 shows the effects of human capital on the quality aspect of co-authorship. The result says that for every 1% increase of human capital, the average coauthor human capital increases by 0.305%. The effects are statistically significant.

	(1)	(2)	(3)	(4)	(5)
$log(H_rt)$	0.011***	0.091***	0.146***	0.151***	0.305***
	(0.002)	(0.005)	(0.010)	(0.011)	(0.011)
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Obs	42,982	42,982	42,982	40,300	40,034
R-sq	0.0072	0.0139	0.0053	0.0068	0.1329

(1) Dependent variable: the number of solo papers
(2) Dependent variable: the number of co-authored papers
(3) Dependent variable: the number of coauthors
(4) Dependent variable: the average number of coauthors per paper
(5) Dependent variable: log(the average human capital of coauthors)
*significant at 10%, **significant at 5%, ***significant at 1%

Table 23: Human capital and the quantity and quality of co-authorship, OLS regression

Table 24 compares solo-papers and co-authored papers. Co-authored papers are older, shorter, published in more prestigious journals, and have more citations. Overall, co-authored papers have a higher quality measure, q. We do not find significant differences in the average human capital and the average absolute deviance in human capital among authors between solo-papers and co-authored papers.

	Number of authors = 1		Number of authors > 1		
	Mean	Std.Dev.	Mean	Std.Dev.	
Age	4.844	3.250	5.736	3.067	***
Average H_r	0.986	0.747	0.977	0.598	
Average absolute deviance in H_r	0	0	0.257	0.284	
q	0.651	1.571	0.902	1.955	***
Times cited	16.077	37.021	24.205	48.012	***
SJR	4.100	3.751	3.973	3.812	**
Pages	22.023	11.025	20.026	10.409	***
Obs	6,660		44,852		

Note: q is the quality of the paper.
It is calculated according to equation (5).
*significant at 10%, **significant at 5%, ***significant at 1%

Table 24: Comparison between solo-authored papers and co-authored papers

3.4.3 Result: Paper Production Function

Table 25 reports the estimates of the paper production function, splitting the results by the number of authors. The number of authors significantly increases the quality of the paper. The point estimate of the substitution parameter ρ for the full sample is around -0.037, implying the elasticity of substitution between researchers of 0.964. Thus, our results suggest that researchers are imperfect complements. Our estimate of the elasticity of substitution is smaller than that between different types of workers. The estimates of the elasticity of substitution range from 1.2 to 2 between skilled and unskilled workers, from 20 to 30 between immigrants and native workers, and from 1 to 1.4 between male and female workers. The elasticity of substitution between researchers is relatively small due to the nature of work that researchers do. The high degree of complexity of economic research requires researchers to specialize in a small set of tasks, which makes it hard to replace one researcher with another. Plus, research teams often consist of researchers with the comparative advantage on different tasks because otherwise, it will be better for them to work by themselves.

	All	Duet	Trio	Quartet	Quintet
b_1	0.447***				
	(0.024)				
b_2	-0.019***	-0.018***	-0.036***	-0.021***	-0.004
	(0.001)	(0.001)	(0.004)	(0.006)	(0.004)
ρ	-0.037	-0.036	-0.073	-0.042	-0.008
σ	0.964	0.965	0.932	0.960	0.992
	[0.963,0.965]	[0.964,0.967]	[0.929,0.935]	[0.955,0.965]	[0.987,0.996]
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Obs	44,852	22,597	16,147	4,960	1,148
R-sq	0.039	0.034	0.044	0.029	0.044

The substitution parameter ρ is calculated as $2b_2$. $b_1 = \beta$.
The elasticity of substitution σ is calculated as $\frac{1}{1-\rho}$.
One standard deviation confidence intervals in brackets are obtained using the delta method.
*significant at 10%, **significant at 5%, ***significant at 1%

Table 25: CES production function, OLS regression

3.5 Collaboration and Research Productivity

In this section, we investigate the effects of collaboration among researchers on human capital. With the estimated parameters and human capital of researchers, we simulate human capital growth under various scenarios.

First, we compare two different scenarios. We consider a researcher whose human capital is in the 50th percentile in period t. In scenario 1, the researcher produces one solo paper. In scenario 2, the researcher produces one co-authored paper with one coauthor whose human capital is also in the 50th percentile. We then compare the growth of researcher's human capital over time between the two scenarios. After the initial collaboration, the growth paths of the number of papers, coauthors, and the average coauthor human capital are determined by the percent increase in human capital and the estimates from section 4.2. For instance, the average coauthor human capital of researcher r increases by $(0.305)(100)\frac{H_{rt+1}-H_{rt}}{H_{rt}}$ from period t to period $t+1$.

As shown in the top panel in Figure 5, the researcher experiences higher and faster human capital growth in scenario 2 than in scenario 1. The bottom panel in Figure 26 plots the percentage difference in human capital between the two scenarios. In period t, collaboration generates 28% higher human capital than solo work. This 'teamwork premium' reaches around 49% in period $t+5$ and slowly decreases thereafter.

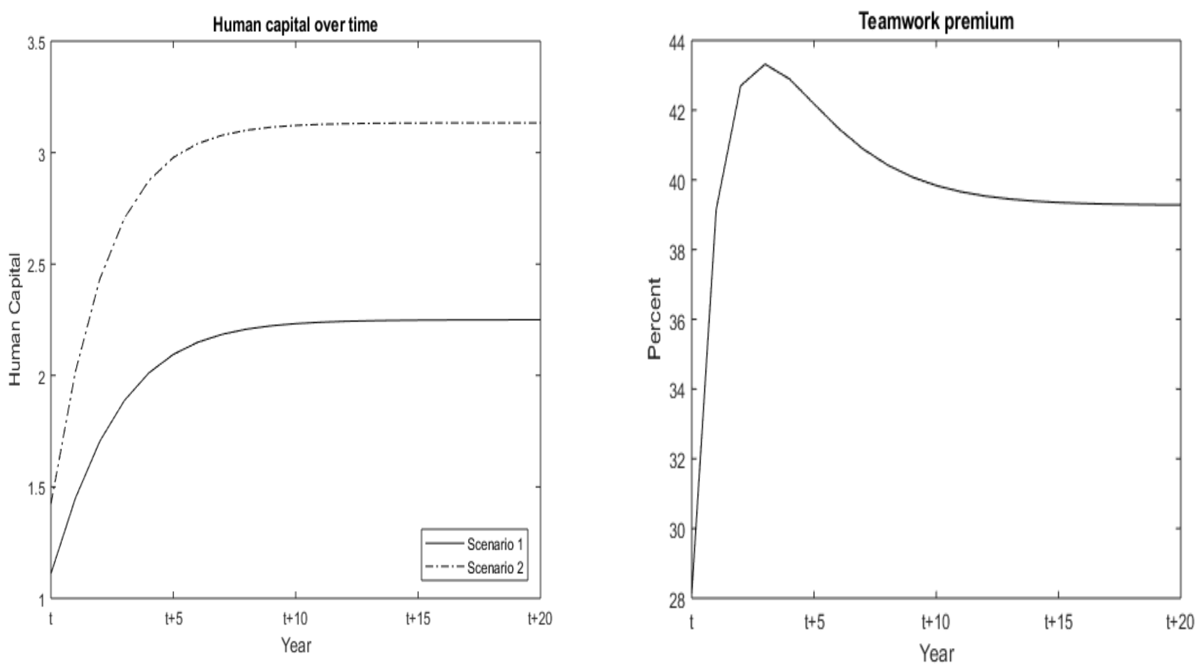


Figure 26: Comparison of the human capital growth between solo-work and co-work

The effects of collaboration persist over time. A rise in human capital from the initial collaboration gives the researcher more collaboration opportunities with more productive researchers, which leads to even more growth of human capital. As shown in Figure 27, the researcher in scenario 2 participates in more co-authorship and works with more productive coauthors throughout research life. To have a closer look at the source of the long-run effects of collaboration, we do a counterfactual analysis where we ignore the link between human capital and the quantity and quality of co-authorship. We assume from period $t+1$ on, the researcher produces one solo paper and one co-authored paper every period. The average coauthor human capital is fixed at period t level. Figure 28 plots the teamwork premium in this case. The benefits of collaboration do not last long. The teamwork premium decreases quickly with time.

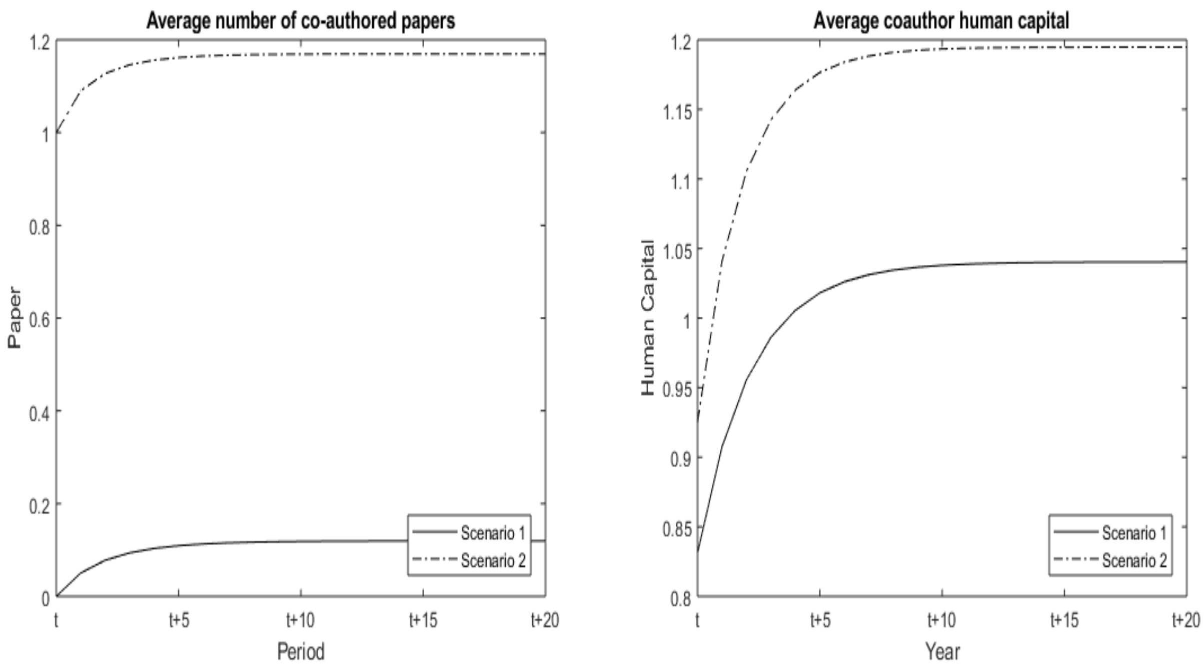


Figure 27: Collaboration and the quantity and quality of co-authorship over time

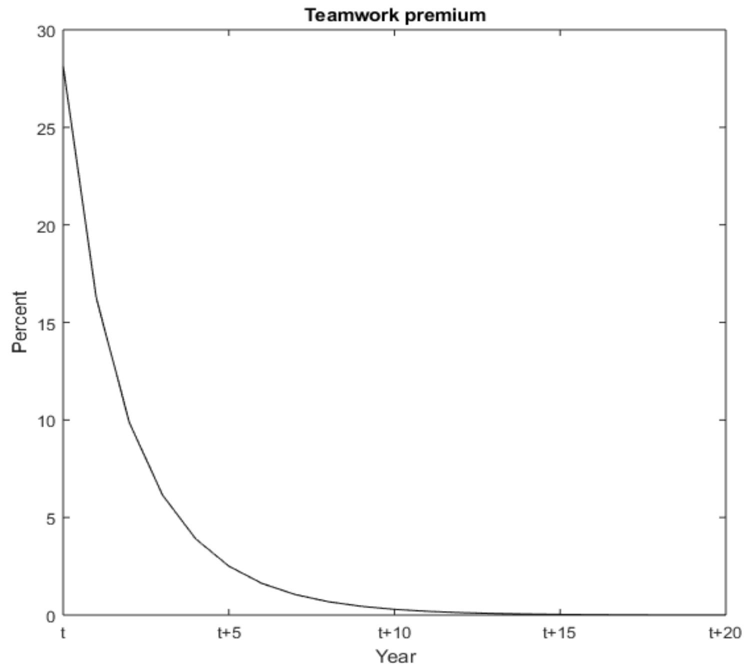


Figure 28: Teamwork premium with an exogenous co-authorship formation

The benefits of collaboration can vary across different types of individuals. Ductor (2015) argues that more-able researchers can enjoy the benefit from collaboration to a greater extent because more able authors tend to have highly productive co-authors while less able authors collaborate with low-productivity researchers. We revisit this argument by controlling for the productivity of coauthors. We calculate the teamwork premium of collaborating with an equally productive coauthor by researchers' human capital. Figure 29 presents the results. Observing equally productive pairs, we find that the immediate benefits of collaboration are actually bigger for low productivity researchers. However, in the long run, highly productive researchers benefit more from collaboration.

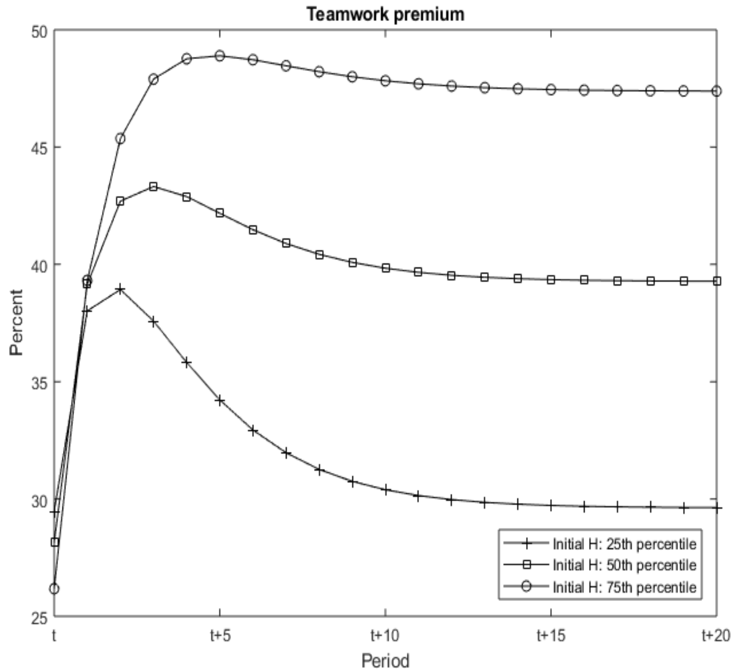


Figure 29: Teamwork premium by human capital

The benefits of collaboration can also differ according to coauthors' human capital. We assign coauthors with different human capital to a researcher with the median human capital and see how his human capital evolves over time. The results are presented in Figure 30. We find that collaborating with more productive researchers generates higher teamwork premium. Collaboration with an equally productive researcher yields about 40% of teamwork premium on average. Having a more productive researcher whose human capital is in the 75th percentile increases the premium to about 51%. Working with a low-productivity researcher, on the contrary, decreases the premium to about 29%.

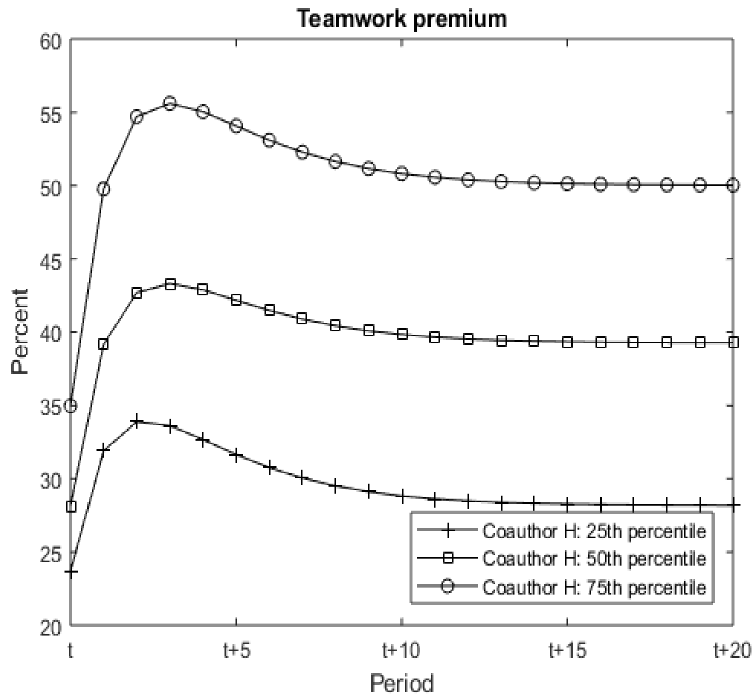


Figure 30: Teamwork premium by coauthor's human capital

Figure 31 plots the teamwork premium by the number of coauthors. We assume the researchers' human capital is all in the 50th percentile. We find that the teamwork premium decreases with the number of coauthors. Collaborating with two equally productive coauthors decreases the teamwork premium to 32%. Adding one more equally productive coauthor decreases the teamwork premium further to 29%.

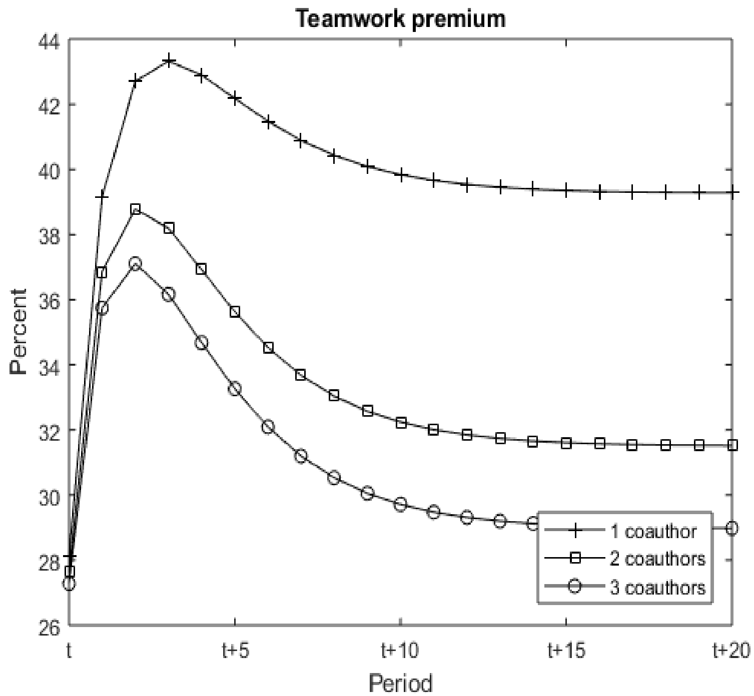


Figure 31: Teamwork premium by the number of coauthors

3.6 Conclusion

In this paper, we investigate the relationship between academic collaboration and research productivity. We specify the human capital function of researchers and the production function of research outcomes. In our framework, researchers' human capital is a function of their publication histories. Once a group of researchers decides to collaborate, their human capital is combined in the manner of CES and produces a research outcome. The elasticity of substitution parameter in the research outcome production function measures the degree of complementarities between any two researchers.

We estimate the researchers' human capital function and the research outcome production function using the data on published articles in the field of Economics and Business. The estimated value of the elasticity of substitution suggests that researchers are imperfect complements. To our knowledge, this is the first attempt to estimate the elasticity of substitution between academics.

The estimated functions show that academia consists of a large number of researchers with low human capital and only a few researchers with high human capital. We also find that collaboration mostly takes place among equally productive researchers. Human capital is closely related to the amount of co-authorship and the quality of coauthors. We show evidence that researchers with higher human capital produce more co-authored papers with more productive coauthors. A 1% increase in human capital is associated with a 0.3% increase in coauthors' human capital.

We then simulate the growth of human capital of a researcher under different collaboration scenarios. We assign a researcher with the median human capital a different set of coauthors and observe how his human capital grows over time. The researcher's human capital is around 40% higher when collaborating with an equally productive coauthor than working by himself. This teamwork premium persists over time. The persistence stems from the fact that the initial increase of human capital from collaboration translates into more collaboration opportunities with more productive coauthors.

The effects of collaboration vary by researchers' own human capital, the coauthors' human capital, and the number of coauthors. We find that low productivity researchers benefit more from collaboration with an equally productive researcher in the short run. However it is the highly productive researchers who benefit more in the long run. Collaboration with more productive researchers yields a higher teamwork premium. Collaboration with more than one coauthor decreases the teamwork premium.

Appendix A Chapter 1

A.1 Value Functions for High-skill Workers

A.1.1 Unemployed Workers

$$
\begin{aligned}
U_t^h(a,b,j) = \max_{a'} u(c, L_u) &+ \chi\beta[\max_{\mu'} m(\theta_{t+1}(h,j,\mu'))E_{t+1}^h(a',\mu',j) \\
&+ (1 - m(\theta_{t+1}(h,j,\mu')))U_{t+1}^l(a',\mu',j)] + (1-\chi)\beta[\max_{\mu'} m(\theta_{t+1}(h,j,\mu'))E_{t+1}^h(a',\mu',j) \\
&+ (1 - m(\theta_{t+1}(h,j,\mu')))U_{t+1}^l(a',\mu',j)], \quad t \leq T
\end{aligned}
$$

$$U_{T+1}^h(a,b,j) = 0$$

$$\text{s.t} \qquad c + a' = (1+r)a + b \quad \text{and} \quad a' \geq \underline{a}$$

A.1.2 Employed Workers

$$E_t^h(a,\mu,j) = \max_{a'} u(c, L_e) + \beta[\delta_j U_{t+1}^h(a',b,j) + (1-\delta_j)E_{t+1}^h(a',\mu,j)], \quad t \leq T$$

$$E_{T+1}^h(a,\mu,j) = 0$$

$$\text{s.t} \qquad c + a' = (1+r)a + (1-\tau)w(\theta_t(h,j,\mu)) \quad \text{and} \quad a' \geq \underline{a}$$

A.2 Additional Tables and Figures

	All		Non participants		Participants		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	
Age	30.14	5.23	29.58	4.57	27.88	4.17	***
Percent male	46.94	0.50	47.32	0.50	21.43	0.41	***
Percent black	18.19	0.39	18.17	0.39	19.05	0.39	
Percent Hispanic	30.89	0.46	30.90	46.21	30.36	0.46	
Percent married	44.42	0.50	44.5	0.50	0.39	0.49	
Total real asset ($)	37791.74	116007.9	37916.3	116630	29514.05	61591.31	
Residual total asset($)	0.00001	112385.5	14.90	113031.9	-989.9683	54456.05	
Real hourly wages($)	12.58	29.62	12.58	29.59	12.92	31.40	
Residual wages($)	-6.57E-09	29.56	-0.02	29.54	1.28	31.20	
Percent non-routine cognitive	17.02	0.38	16.93	0.38	23.21	42.35	**
Percent non-routine manual	18.13	0.39	18.00	0.38	26.19	0.44	***
Percent routine cognitive	26.36	0.44	26.18	0.44	38.10	0.49	***
Percent routine manual	38.49	0.49	38.89	0.49	12.50	0.33	***
AFQT	37734.65	24876.11	37626.06	24849.87	44979.19	25625.52	***
N of Obs	11,332		11,164		168		

Note: *Significant at 10%, **Significant at 5%, ***Significant at 1%
Source: NLSY79.

Table 26: Descriptive statistics

A. Male	Non-participants	Participants	
Percent non-routine cognitive	12.99	27.78	***
Percent non-routine manual	12.44	11.11	
Percent routine cognitive	10.81	25.00	***
Percent routine manual	63.77	36.11	***
B. Female	**Non-participants**	**Participants**	
Percent non-routine cognitive	20.47	21.97	
Percent non-routine manual	23.01	30.30	**
Percent routine cognitive	40.00	41.67	
Percent routine manual	16.53	6.06	***

*significant at 10%, **significant at 5%, ***significant at 1%
The corresponding table for the NLSY79 can be found in the Appendix.
Source: NLSY79.

Table 27: Occupation by sex (participants vs. non-participants)

Age	Asset	Low-skill		
		Employed	Unemployed	
			Participants	Non-participants
18-22	1st quartile	-0.006	-0.002	-0.001
	2nd quartile	-0.005	-0.002	-0.003
	3rd quartile	-0.019	-0.008	-0.001
	4th quartile	-0.147	-0.037	-0.001
23-27	1st quartile	-3.76E-04	-0.003	-4.52E-05
	2nd quartile	-7.43E-04	-0.003	-2.07E-04
	3rd quartile	-0.003	-0.014	-3.12E-04
	4th quartile	-0.183	-0.114	-0.001
28-32	1st quartile	-3.48E-05	-0.002	-4.70E-06
	2nd quartile	-1.22E-04	-0.001	-1.67E-05
	3rd quartile	-4.06E-04	-0.007	-5.73E-05
	4th quartile	-0.076	-0.056	-3.41E-04
33-37	1st quartile	-1.81E-05	-4.54E-04	-6.24E-06
	2nd quartile	-1.07E-04	-4.38E-04	-4.48E-06
	3rd quartile	-4.77E-06	-0.003	-3.01E-07
	4th quartile	-0.020	-0.020	-5.71E-05
38-42	1st quartile	-2.24E-05	-2.32E-05	-7.77E-06
	2nd quartile	-1.11E-04	-5.51E-05	-5.53E-06
	3rd quartile	-2.22E-05	-6.44E-04	-1.12E-06
	4th quartile	-0.005	-0.005	-4.51E-06
43-47	1st quartile	-1.50E-05	0.000	-5.37E-06
	2nd quartile	-6.58E-05	0.000	-5.91E-06
	3rd quartile	-6.28E-05	-2.79E-05	-5.25E-06
	4th quartile	-0.001	-2.60E-04	-1.16E-05
48-52	1st quartile	-8.84E-06	0.000	-7.95E-07
	2nd quartile	-7.17E-05	0.000	-1.18E-06
	3rd quartile	-0.005	0.000	-1.49E-04
	4th quartile	-0.005	0.000	-1.45E-04
Overall		-0.475	-0.277	-0.009

Note: This table presents detailed welfare analysis of scenario 2 in Table 12. Results reported as change(%) in the remaining lifetime consumption relative to the benchmark economy.

Table 28: Welfare changes for low-skill workers, tax effects excluded

Age	Asset	Low-skill		
		Employed	Unemployed	
			Participants	Non-participants
18-22	1st quartile	-0.018	-0.002	-0.006
	2nd quartile	-0.030	-0.002	-0.007
	3rd quartile	-0.023	-0.008	-0.002
	4th quartile	-0.158	-0.039	-0.002
23-27	1st quartile	-0.006	-0.003	-0.002
	2nd quartile	-0.030	-0.003	-0.002
	3rd quartile	-0.003	-0.014	-4.89E-04
	4th quartile	-0.190	-0.117	-0.001
28-32	1st quartile	-0.005	-0.002	-0.002
	2nd quartile	-0.028	-0.001	-0.001
	3rd quartile	-0.001	-0.007	-9.80E-05
	4th quartile	-0.078	-0.057	-4.21E-04
33-37	1st quartile	-0.005	-4.55E-04	-0.002
	2nd quartile	-0.028	-4.39E-04	-0.001
	3rd quartile	-1.25E-04	-0.003	-1.38E-05
	4th quartile	-0.020	-0.020	-6.63E-05
38-42	1st quartile	-0.005	-2.32E-05	-0.002
	2nd quartile	-0.023	-5.51E-05	-0.001
	3rd quartile	-0.003	-0.001	-1.91E-04
	4th quartile	-0.010	-0.005	-1.30E-04
43-47	1st quartile	-0.002	0.000	-0.001
	2nd quartile	-0.011	0.000	-0.001
	3rd quartile	-0.005	-2.80E-05	-0.001
	4th quartile	-0.033	-2.60E-04	-0.001
48-52	1st quartile	-1.76E-04	0.000	-4.58E-05
	2nd quartile	-3.96E-04	0.000	-3.38E-05
	3rd quartile	-0.014	0.000	-3.70E-04
	4th quartile	-0.053	0.000	-0.001
Overall		-0.779	-0.283	-0.035

Note: This table presents detailed welfare analysis of scenario 3 in Table 12. Results reported as change(%) in the remaining lifetime consumption relative to the benchmark economy.

Table 29: Welfare changes for low-skill workers, firm choice effects excluded

Age	Asset	Low-skill		
		Employed	Unemployed	
			Participants	Non-participants
18-22	1st quartile	-0.018	-0.002	-0.006
	2nd quartile	-0.029	-0.002	-0.007
	3rd quartile	-0.027	-0.008	-0.002
	4th quartile	-0.158	-0.039	-0.002
23-27	1st quartile	-0.006	-0.003	-0.002
	2nd quartile	-0.029	-0.003	-0.002
	3rd quartile	-0.004	-0.014	-4.74E-04
	4th quartile	-0.187	-0.116	-0.001
28-32	1st quartile	-0.005	-0.002	-0.002
	2nd quartile	-0.028	-0.001	-0.001
	3rd quartile	-0.001	-0.007	-9.65E-05
	4th quartile	-0.077	-0.056	-3.93E-04
33-37	1st quartile	-0.005	-4.55E-04	-0.002
	2nd quartile	-0.028	-4.39E-04	-0.001
	3rd quartile	0.000	-0.003	-1.38E-05
	4th quartile	-0.020	-0.020	-6.63E-05
38-42	1st quartile	-0.005	-2.32E-05	-0.002
	2nd quartile	-0.023	-5.51E-05	-0.001
	3rd quartile	-0.003	-0.001	-1.91E-04
	4th quartile	-0.017	-0.005	-1.30E-04
43-47	1st quartile	-0.002	0.00	-0.001
	2nd quartile	-0.011	0.00	-0.001
	3rd quartile	-0.005	-2.80E-05	-0.001
	4th quartile	-0.033	-2.60E-04	-0.001
48-52	1st quartile	-1.76E-04	0.00	-4.57E-05
	2nd quartile	-3.96E-04	0.00	-3.37E-05
	3rd quartile	-0.014	0.00	-3.70E-04
	4th quartile	-0.053	0.00	-0.001
Overall		-0.786	-0.281	-0.034

Note: This table presents detailed welfare analysis of scenario 4 in Table 12. Results reported as change(%) in the remaining lifetime consumption relative to the benchmark economy.

Table 30: Welfare changes for low-skill workers, saving effects excluded

		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5
18-22	1st quartile	0.1226	0.0776	0.0974	0.2455	0.0771
	2nd quartile	0.0998	0.0469	0.0506	0.1358	0.0522
	3rd quartile	0.0750	0.0335	0.0347	0.1040	0.0300
	4th quartile	0.1417	0.0547	0.0506	0.2029	0.0430
23-27	1st quartile	0.0524	0.0504	0.0683	0.1464	0.0579
	2nd quartile	0.0602	0.0306	0.0339	0.0832	0.0433
	3rd quartile	0.0601	0.0266	0.0293	0.0889	0.0360
	4th quartile	0.3294	0.1178	0.1108	0.4852	0.1279
28-32	1st quartile	-0.0019	0.0299	0.0453	0.0652	0.0294
	2nd quartile	0.0406	0.0218	0.0251	0.0587	0.0384
	3rd quartile	0.0403	0.0202	0.0235	0.0652	0.0364
	4th quartile	0.2116	0.0801	0.0815	0.3338	0.1733
33-37	1st quartile	-0.0370	0.0159	0.0278	0.0042	-0.0044
	2nd quartile	0.0187	0.0122	0.0157	0.0340	0.0257
	3rd quartile	0.0183	0.0124	0.0162	0.0389	0.0307
	4th quartile	0.0917	0.0403	0.0467	0.1815	0.1402
38-42	1st quartile	-0.0309	0.0078	0.0165	-0.0141	-0.0104
	2nd quartile	-0.0081	0.0043	0.0064	8.6706e-04	1.8953e-04
	3rd quartile	-0.0102	0.0048	0.0084	5.1245e-04	0.0018
	4th quartile	-0.0216	0.0123	0.0209	0.0196	0.0143
43-47	1st quartile	-0.0096	0.0022	0.0092	-0.0124	-0.0033
	2nd quartile	-0.0075	0.0018	0.0042	-0.0139	-0.0026
	3rd quartile	-0.0238	0.0056	0.0134	-0.0428	-0.0083
	4th quartile	-0.1314	0.0207	0.0481	-0.0506	-0.0322
48-52	1st quartile	-0.0023	5.2379e-04	0.005	-0.1299	-7.8855e-04
	2nd quartile	-0.0739	0.0273	0.4620	-0.6172	-0.0255
	3rd quartile	-0.0656	0.1300	0.0564	-0.3914	-0.0290
	4th quartile	-0.0476	0.0129	0.0308	-0.0840	-0.0237
	Overall	0.8913	0.9012	1.4545	0.9383	0.8174

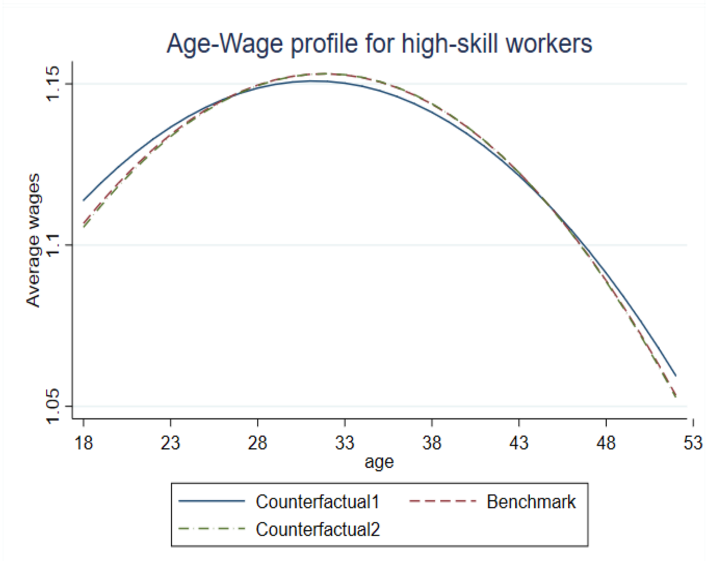
Note: Policy 1: Government pays all the retraining costs. Policy 2: Retraining participants can receive unemployment benefit for a longer period of time than non-participants (up to two years). Policy 3: Retraining participants can receive higher unemployment benefit than non-participants Policy 4: No UI benefit + free retraining Policy 5: Government pays retraining costs only for selected population (older and/or low-assets)
Results reported as percent change (percentage point change in case of retraining rate) relative to the benchmark scenario.

Table 31: Comparison in welfare across policies (low-skill workers)

		Policy 1	Policy 2	Policy 3	Policy 4	Policy 5
18-22	1st quartile	-0.4963	0.1457	0.1982	-0.0938	-0.2122
	2nd quartile	-0.4458	0.0743	0.1065	-0.0376	-0.1506
	3rd quartile	-0.0765	0.0166	0.0237	-0.0069	-0.0257
	4th quartile	-0.0015	3.2954e-04	4.7050e-04	-1.3884e-04	-5.0454e-04
23-27	1st quartile	-0.1270	0.0659	0.1617	-0.0277	-0.2651
	2nd quartile	-0.4365	0.0752	0.0866	-0.0266	-0.1244
	3rd quartile	-0.1367	0.0292	0.0416	-0.0123	-0.0455
	4th quartile	-0.0256	0.0057	0.0081	-0.0025	-0.0087
28-32	1st quartile	-0.0331	0.0095	0.0143	-0.0077	-0.0125
	2nd quartile	-1.1446	0.5707	0.1658	-0.0555	-0.1692
	3rd quartile	-0.2423	0.0375	0.0522	-0.0186	-0.0854
	4th quartile	-0.0629	0.0141	0.0202	-0.0067	-0.0215
33-37	1st quartile	-0.0214	0.0052	0.0075	-0.0053	-0.0076
	2nd quartile	-0.4652	0.0557	0.1077	-0.1901	-0.0957
	3rd quartile	-0.2579	0.0606	0.1123	-0.0658	-0.1305
	4th quartile	-0.0873	0.0197	0.0282	-0.0105	-0.0300
38-42	1st quartile	-0.0116	0.0028	0.0040	-0.0033	-0.0041
	2nd quartile	-0.1353	0.0491	0.0601	-0.0165	-0.1812
	3rd quartile	-0.5483	0.0722	0.0919	-0.0675	-0.1394
	4th quartile	-0.1109	0.0247	0.0353	-0.0162	-0.0377
43-47	1st quartile	-0.0036	8.5922e-04	0.0012	-0.0014	-0.0013
	2nd quartile	-0.0391	0.0096	0.0207	-0.0092	-0.0167
	3rd quartile	-0.2749	0.0415	0.0794	-0.0619	-0.0554
	4th quartile	-0.3345	0.0613	0.0950	-0.0746	-0.0642
48-52	1st quartile	-3.8490e-04	8.9205e-05	1.2788e-04	-0.0169	-1.3426e-04
	2nd quartile	-0.0351	0.0147	0.0534	-1.4407	-0.0113
	3rd quartile	-0.3295	0.0365	0.0756	-0.5124	-0.0877
	4th quartile	-0.0267	0.0055	0.0076	-0.0154	-0.0088
	Overall	-5.9104	1.5051	1.6595	-2.8038	-1.9930

Note: Policy 1: Government pays all the retraining costs. Policy 2: Retraining participants can receive unemployment benefit for a longer period of time than non-participants (up to two years). Policy 3: Retraining participants can receive higher unemployment benefit than non-participants Policy 4: No UI benefit + free retraining Policy 5: Government pays retraining costs only for selected population (older and/or low-assets)
Results reported as percent change (percentage point change in case of retraining rate) relative to the benchmark scenario.

Table 32: Comparison in welfare across policies (high-skill workers)



Counterfactual 1: an economy with a high retraining completion rate, Benchmark: an economy with a low retraining completion rate, Counterfactual 2 : an economy where retraining doesn't exist.

Figure 32: Age-wage profiles by skill

A.3 Solution Algorithm

Starting at $t = T$ and working backwards, the solution is given as:

1. Compute the firm value function, $J_t(s, j, \mu)$.
2. Computer the market tightness, $\theta_t(s, j, \mu)$, by equation (9).
3. Guess a value for the income tax rate, τ.
4. Solve the employed high-skill worker problem for all t, a, μ, j and compute optimal savings $a^h_{t+1}(a_t, \mu, j)$.
5. Solve the unemployed high-skill worker problem for all t, a, b, j and compute optimal savings $a^h_{t+1}(a_t, b, j)$ and optimal firm choices $\theta^h_{t+1}(a_t, b, j)$.
6. Solve the employed low-skill worker problem for all t, a, μ, ψ, j and compute optimal savings $a^l_{t+1}(a_t, \mu, \psi, j)$.
7. Solve the low-skill non-participant problem for all t, a, μ, ψ, j and compute optimal savings $a^l_{t+1}(a_t, \mu, \psi, j)$ and optimal firm choices $\theta^l_{t+1}(a_t, b, \psi, j)$.
8. Solve the low-skill participant problem for all t, a, μ, ψ, j, z and compute optimal savings $a^l_{t+1}(a_t, \mu, \psi, j, z)$ and optimal firm choices $\theta^l_{t+1}(a_t, b, \psi, j, z)$.
9. Solve the retraining decision for low-skill unemployed workers and recover $D_t(a, b, \psi, j)$.
10. Using the policy functions, compute the distribution functions over the state variables.
11. Using the policy functions and distribution functions, compute the total tax revenue and government expenditure on unemployment insurance benefit. Check if the government budget is balanced.
12. If the government budget is balanced, the model is solved. If not, go back to 3 and adjust the tax rate.

Appendix B Chapter 3

	Journal	SJR
1	Quarterly Journal of Economics	30.490
2	Journal of Political Economy	22.902
3	Journal of Finance	17.973
4	Econometrica	17.635
5	Review of Economic Studies	14.499
6	Journal of Financial Economics	13.636
7	Journal of Labor Economics	13.590
8	Review of Financial Studies	12.516
9	Journal of Human Resources	12.363
10	American Economic Review	11.889
11	Journal of Accounting Research	10.151
12	Journal of Marketing	9.198
13	Journal of Economic Literature	9.194
14	Annual Review of Economics	8.790
15	Review of Economics and Statistics	8.363
16	Journal of Monetary Economics	7.248
17	Journal of Marketing Research	6.895
18	Marketing Science	6.853
19	Journal of Accounting and Economics	6.606
20	Journal of Consumer Research	6.590
21	Journal of Economic Growth	6.312
22	Journal of Economic Perspectives	6.085
23	Journal of International Business Studies	5.548
24	Accounting Review	5.240
25	Quantitative Economics	5.177
26	Entrepreneurship: Theory and Practice	5.073
27	Economic Journal	5.009
28	Review of Economic Dynamics	4.990
29	Journal of the Academy of Marketing Science	4.801
30	Brookings Papers on Economic Activity	4.663
31	Annual Review of Financial Economics	4.584
32	Journal of Econometrics	4.485
33	International Economic Review	4.376

continued ...

	Journal	SJR
34	RAND Journal of Economics	4.376
35	Journal of International Economics	4.347
36	Economic Policy	4.169
37	Journal of Financial and Quantitative Analysis	3.986
38	Journal of Public Economics	3.691
39	Journal of Financial Intermediation	3.514
40	Journal of Economic Theory	3.467
41	Review of Finance	3.465
42	Journal of Risk and Uncertainty	3.449
43	Journal of Development Economics	3.432
44	Economic Geography	2.915
45	Journal of Economic Geography	2.902
46	Contemporary Accounting Research	2.895
47	Journal of Business and Economic Statistics	2.886
48	Journal of International Marketing	2.866
49	Mathematical Finance	2.834
50	Journal of Applied Econometrics	2.817
51	Strategic Entrepreneurship Journal	2.817
52	Econometric Theory	2.810
53	Review of Environmental Economics and Policy	2.772
54	Journal of Urban Economics	2.724
55	Real Estate Economics	2.531
56	International Journal of Production Economics	2.475
57	Auditing	2.417
58	Journal of Money, Credit and Banking	2.357
59	Journal of Financial Econometrics	2.282
60	World Development	2.254
61	Journal of Environmental Economics and Management	2.232
62	European Economic Review	2.210
63	Economic Development and Cultural Change	2.174
64	Conflict Management and Peace Science	2.140
65	Journal of Economic History	2.117
66	Economics of Education Review	2.098
67	Economica	2.087
68	Cambridge Journal of Regions, Economy and Society	2.083
69	Review of International Organizations	2.053
70	Economic Theory	2.032
71	Journal of Common Market Studies	2.017
72	Energy Economics	2.003

continued . . .

	Journal	SJR
73	Review of International Political Economy	1.935
74	Small Business Economics	1.913
75	American Journal of Agricultural Economics	1.906
76	Annual Review of Resource Economics	1.894
77	Journal of Law, Economics, and Organization	1.888
78	Journal of Business Ethics	1.860
79	Journal of Economic Surveys	1.847
80	Agricultural Economics	1.815
81	Journal of Law and Economics	1.815
82	Scandinavian Journal of Economics	1.815
83	Games and Economic Behavior	1.814
84	Econometrics Journal	1.813
85	Post-Soviet Affairs	1.790
86	Food Policy	1.782
87	Ecological Economics	1.767
88	World Bank Economic Review	1.757
89	Journal of Corporate Finance	1.748
90	Economic Systems Research	1.738
91	Business Ethics	1.723
92	Journal of Economic Behavior and Organization	1.714
93	Science Technology and Human Values	1.714
94	Journal of the Royal Statistical Society. Series A, (Statistics in Society)	1.690
95	Journal of Family Business Strategy	1.683
96	Work, Employment and Society	1.644
97	International Journal of Electronic Commerce	1.634
98	Judgment and Decision Making	1.601
99	Journal of Banking and Finance	1.599
100	Journal of Demographic Economics	1.581

Table 33: Journal list

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