When Work is Threatened: Lifelong Education and Occupation Choice

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Preliminary and incomplete. Please do not circulate.

Abstract

We study the role of adult apprenticeship in occupation choice using matched Danish adult and continuing education register and employer-employee data. A dynamic difference-in-difference reveals that manufacturing workers enrolled in apprenticeships related to business service (BS) occupations exhibit a 0.9-3.1 percentage point higher probability of transitioning to BS occupations in 1-8 years, compared to non-participants. We propose and estimate a life-cycle model of occupation and program choices that yields a logit conditional choice probability with flexible elasticities of the program choice. The estimated program take-up elasticity is lower than that of occupation choice, suggesting a relative insensitivity of individuals to the program value. A counterfactual wage subsidy policy conditional on BS-related program take-up facilitates switches from traditional manufacturing jobs to BS occupations, underscoring the potential benefits of adult training policies to address the recent changes in labor markets, such as structural changes and automation.

Keywords: Adult apprenticeship, Dynamic difference-in-difference, Life-cycle model.

JEL codes: J24, J62, I21

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1 Introduction

Recent changes in labor markets, such as structural transformation, automation, and offshoring, have revived discussions about adult education. Concerns have emerged regarding the loss of jobs in certain industries, such as traditional manufacturing and routine work. If job transitions of these workers are costly, these labor market changes may be excessive, and an optimal policy might slow down the pace of these changes. In this paper, we argue that adult vocational training may mitigate this concern by nurturing new skills rewarded in labor markets to those with obsolete skills and encouraging them to move into other growing occupations. Given this potential, policymakers seek the education system to be resilient to labor market shocks. However, there has been no formal method to assess adult training policy quantitatively. To fill this gap, we propose a framework to study the role of adult vocational training on workers' occupation choices.

We approach this question in the context of the Danish adult vocational apprenticeship programs, which provide a wide range of skills relevant to employment to new learners with age equal to or above 25. To capture the heterogeneity of vocational skills covered in the programs, we follow the Danish education classification and provide its matching with occupation codes. Applying the classification and matching to the Danish administrative employer-employee matched data, we can analyze the dynamic correlation patterns of apprenticeship program take-up, occupation choices, and earnings trajectory.

To control for individual heterogeneity that biases treatment effect estimates, we match samples on employment history. Specifically, for each education category, previous occupation, and treatment year, we define an estimation sample as those with work experience in the previous occupation for five years up to the treatment year. Among this sample, those who participate in a program in the education category are grouped in the treatment, while others are in the control group. Given these, we estimate a dynamic treatment effect of program participation on occupational employment transitions by the local-projection difference-in-difference (DiD) approach. We find that among workers in the Manufacturing and Technology occupations, participants of Business Services (BS) education programs move to the BS occupations by 0.9-3.1 percentage points higher than non-participants in 1-8 years, depending on the time horizon.

We then estimate the modified Mincer equation to study the impact on earnings. The Mincer equation is modified to our setting as it includes the indicator variable of apprenticeship program takeup in a specific program category as well as standard potential experience and tenure variables and individual fixed effects, and it is run on the sample of workers in the relevant occupation group. We find that for all occupation groups, tenure is associated with earnings increase by 1-2 percent, consistent with the literature, and on top of that, earnings are higher by 2-3 percent for those who have taken the programs in manufacturing or BS skills than for those who have not. However, since our DiD and Mincer regression analysis are subject to issues of individual workers' selection, and since it does not fully guide the policy counterfactual analysis, we develop a theoretical framework to interpret these empirical findings.

We consider an individual life-cycle model with a discrete choice of participation in apprenticeship programs as well as jobs. The decision to participate in programs affects the level of human capital in the relevant occupations. Forward-looking individuals maximize the expected lifetime utility subject to the preference shock of choosing both occupation and education categories. To solve this decision problem parsimoniously and flexibly, we introduce a correlated Gumbel distribution for preference shocks, which results in closed-form education demand and occupation choice equations similar to those derived from nested CES functions. Namely, the solution is characterized by two sensitivity parameters: the occupation choice sensitivity to the choice-specific value function and the program choice sensitivity conditional on occupation.

To build intuition for the role of training programs in this model, consider two extreme scenarios, the one where there is no training program and the other where there is. In the first scenario, workers tend to work in traditional occupations to accumulate human capital. By contrast, if adult training is more available and attractive, workers do not necessarily have to work to accumulate occupation-specific human capital. In this sense, attractive apprenticeship programs may shift employment in a traditional manufacturing occupation to occupations in which programs aim to develop relevant skills by substituting the mode of human capital accumulation. As is standard in life-cycle models, this effect is stronger for the young since the investment value is larger.

We estimate the model in three steps. First, we apply the finite mixture method and estimate human capital functions. Second, we use the model restrictions of the correlated logit solution and renewal actions to derive the log-linear estimable equation to back out the occupation choice elasticity. These two steps closely follow the strategy of Traiberman (2019). Thirdly, we apply a similar idea to the second step and derive the estimable equation for the conditional program change sensitivity. The key idea is to condition value functions on the occupation choice to control for different tenure paths and directly measure the choice-specific value function using already estimated parameters.

As a result, we find a qualitatively similar value for the occupation choice sensitivity, which confirms the robustness of the past study. Furthermore, we find that the education switching elasticity is lower than the occupation choice elasticity, especially for those not employed. This result suggests a relative insensitivity of individuals to the program's attractiveness. The estimated model explains more than half of the observed variations of the choice probability of occupations and programs. Thus, it provides a solid basis to evaluate the impact of policy reforms on training program take-up, occupation shares, and individuals' welfare over the life cycle.

To demonstrate this point, we examine the effect of counterfactual wage subsidy policy changes. We compare two scenarios: one where the subsidy is only conditional on taking any programs, and the other is conditional on taking BS training programs. We find that the first scenario leads to expanding the current employment inequality between occupations, so the manufacturing worker share increases. This is because of the complementarity between the tenure effect and the apprenticeship program effect on occupation-specific human capital development. By contrast, under the second scenario, the share of workers in BS occupations rises sharply, with a strong churning effect where manufacturing occupations decline. This is because of the substitution of human capital development via accumulating the occupation tenure in a traditional occupation to taking the formal apprenticeship programs in different occupations, in this case, BS occupations. Hence, our framework showcases the importance of the design of adult apprenticeship programs in reshaping the labor markets under the swift labor market changes.

This study is related to a large body of literature on evaluating adult training programs.[1] Among others, Heckman et al. (1998a) estimate treatment effects of the 1982 Job Training Partnership Act in the US. In Denmark, Jespersen et al. (2008) analyze the impact of retraining programs for the unemployed on employment and earnings and find that public training programs did not significantly increase employment but increased annual earnings by Danish kroner 9-40 thousand in 1-4 years. However, these previous studies have focused primarily on whether labor market attachment or income increased as a result and have not examined the underlying process of the effect of different types of vocational training on labor mobility between occupations.

Burgeoning literature is looking into training and job switches. For example, Kambourov et al. (2020) argues that the occupational switches associated with government-sponsored training have a positive effect on human capital as well as employer-sponsored ones. Katz et al. (2022) also find substantial earnings gains following WorkAdvance training programs, not just due to rising employment but to participating in higher wage jobs and occupations. We contribute to this literature by providing a theoretical framework to think about occupation-specific human capital development by experience and formal program take-up.

Our paper is most closely related to Schulze (2024), who studies the role of adult enrollment to community colleges in mitigating the Great Recession shocks to the labor market. He finds previous employment history heterogeneity plays a key role in enrollment, and estimate a dynamic discrete choice model of sector and field of study to inform the tuition subsidy policy changes. We complement this paper by studying an adult appren-

[1] Card et al. (2018) provides a review of the recent literature on the performance of government-sponsored training programs.

ticeship rather than college education, which is more directly attached to labor markets. Furthermore, we do not use a labor market shock to shift the enrollment decision but an wage subsidy change that directly affects the apprenticeship take-up but not the returns in the labor market.

More theoretically, this paper is related to the recent literature on labor market dynamics in relation to globalization (among others, Artuç et al., 2010; Dix-Carneiro, 2014; Caliendo et al., 2019; Traiberman, 2019). Building upon the life-cycle dynamic discrete choice models, Traiberman (2019) examines the distributional effect of import competition along occupations. These papers take human capital accumulation in a fairly passive way, as workers can affect the level of skills only by job experiences. In our model, individuals can develop human capital actively by taking training programs to maximize their lifetime earnings and utility. In this setting, we can analyze the role of apprenticeship policies in relation to varying degrees of external shocks.

As far as we are aware, models incorporating the dynamic effect of education on labor market outcomes treat them sequentially instead of simultaneously, motivated by more education programs for youth like university going (e.g., Keane and Wolpin 1997; Heckman et al. 1998b; Lee 2005; Lee and Wolpin 2010). Departing from this tradition, we consider a model of the per-period joint decision of employment and program take-up, reflecting the feature of Danish adult apprenticeship programs.

We also build upon the literature on the analysis of Danish active labor market policies (ALMP, Andersen et al., 2021). Recent contributions include Humlum and Munch (2019), who study the effect of the 2011 subsidy reform and the relationship between take-up and globalization. Kreiner and Svarer (2022) theorize that the success factor of Danish ALMP is the strong emphasis on compulsory participation for unemployment compensation recipients. We provide a matching between the ISCED education classification and the ISCO occupation groups and estimate their treatment effects based on the dynamic difference-in-difference estimation method applied to the matching sample.

2 Background

In this section, we review adult education in Denmark and administrative data sources.

2.1 Adult Vocational Training in Denmark

Denmark spends 2% of its GDP on ALMP, the largest share among OECD countries. An important pillar of the Danish ALMP is adult education, which is open to all individuals in Denmark, independent of their employment status. Danish adult education is historically characterized by a strong vocational and life-long nature, and reforms throughout the 2000s strengthened the emphasis on practical skills closely connected with the labor markets as opposed to general or academic skills (Rasmussen et al., 2019).

We focus on initial vocational education and training (IVET) for adult individuals (CEDEFOP, 2023). In the Danish context, the adult apprenticeship scheme (*Voksenlærlingeordningen*) provides basic vocational skills attached to labor markets for low-skilled individuals. Individuals with an age equal to or more than 25 can use this scheme and take school-based programs as well as on-the-job training under an apprentice contract with a provider. The program is free of charge, and a wage subsidy is provided during the period. The program periods are typically longer than Danish continuing vocational education and training (CVET) counterpart labor market education (*Arbejdsmarkedsuddannelser, AMU*).[2] Our focus on the adult apprenticeship and not including AMU from the analysis is because our interest is studying the long-term effects of adults' development of new skills and considering the adult individuals' (rather than firms') decisions.

Adult apprenticeship programs typically consist of basic courses (*grundforløb*et) and main courses (*hovedforløb*et). The basic courses are prerequisites for main courses, and it depends on past labor market experiences if participants are required to take a basic course. Since completing a main course is a requirement for all programs, we define the

[2] AMU programs are more common to broader populations of employed workers and last only a few days, depending on the sector of employment (Humlum and Munch, 2019). By contrast, adult apprenticeship programs tend to last months and sometimes even years, depending on individuals' past experiences.

program take-up by participation and completion of a main course. Regulations specify that the skills acquired during the apprenticeship should not be depreciated and be applicable in the labor market for at least five years (Danish Agency for Labour Market and Recruitment, 2023).

The main courses contain a variety of training contents. Since we aim to study employment transitions, we distinguish different educational contents for each occupation group. For this purpose, we use the following four categories based on the Danish adoption of the 2015 International Standard Classification of Education (DISCED-15): Agriculture and Food (FJO), Business service (KHF), Personal Service (OSP), and Manufacturing and Technology (TBT), as shown in Table 1. As examples, the top two course names for each category in terms of the number of participants in 2010 are given in Table 1. This classification of vocational training is finer than the ones used in the literature.[3] Finally, based on the manual inspection of the contents of each education group, we classify occupations and construct a one-to-one relationship with education groups, as shown in the last column of Table 1.

Since the Manufacturing and Technology (TBT) programs and Business service (KHF) programs have ample take-up variation, and they are likely to be related to the recent labor market shocks, we mainly focus on these two programs. From now on, we occasionally call the TBT programs and relevant occupations "manufacturing" occupations and the KHF programs and relevant occupations "business-service" (BS) occupations.

We choose to construct a crude occupation classification and a one-to-one mapping with education groups since it clarifies the idea that adult apprenticeship may foster the transition into different occupations. Based on these occupation groups, we find that the average annual transition rates from the manufacturing to BS occupations are 2-4%.

[3] For example, Jacobson et al. (2005) provide a classification of community colleges in Washington State classes into group 1 (quantitative courses) and group 2 (non-quantitative courses). Our classification complements theirs because we provide a more granular vocational education classification but abstract from non-vocational education.

Table 1: Classifications of Education and Occupations

Education group (DISCED tag)	Popular Course Name in 2010	DISCO Occupations
Agriculture and Food (FJO)	Restaurant, canteen and catering	512, 513 (Work in restaurant); 6 (Agriculture)
	Food for varied nutritional needs	
Business service (KHF)	Administration	7 (Craftsmanship); 8 (Machine operator)
	Retail trade	
Personal Service (OSP)	Nursing and educational work	33 (Administration); 41, 43 (Office work)
	Social psychiatry and disability	
Manufacturing and Technology (TBT)	The work organization in industry	32 (Health technician); 53 (Caring work)
	Basic competence driver - goods	

Note: The table shows the classification of education programs with the category tag defined by the Danish adoption of the 2015 International Standard Classification of Education, titles of the most popular courses as of 2010, and corresponding occupations. Tags are abbreviations: FJO abbreviates *Fødevarer, jordbrug og oplevelser*; KHF abbreviates *Kontor, handel og forretningsservice*; OSP abbreviates *Omsorg, sundhed og pædagogik*; and TBT abbreviates *Teknologi, byggeri og transport*.

2.2 Data

We combine Danish administrative data to analyze the adult apprenticeship. Most importantly, we use the Register for Course Participants in Adult and Continuing Education (VEUV). The VEUV register contains all records of publicly subsidized adult education programs in Denmark since 1980 with variables of the education code that can be matched to the education category, the required effort (number of hours) per year, and the start and end dates of the program. We aggregate records at the individual-year level to match other data. In case of multiple courses within a year, we assign the one with the highest hours each year to each individual.

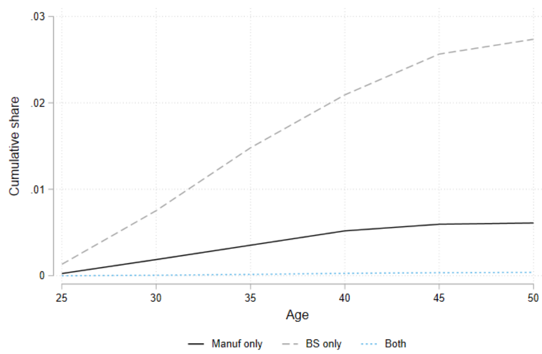
Next, we take employment information from the employer-employee-matched data of the Integrated Database for Labor Market Research (IDA). We use a firm and establishment indicator, firm industry, occupation code, workplace municipality, and yearly earnings variables of the November main jobs from the IDA. Yearly earnings consist of wages subject to labor market contributions. Other standard data sources include the Register-based Labor Force Statistics (RAS), which gives us information about unemployment and those not in the labor force; the Population Register (BEF), which contains demographic information such as age, sex, and immigration status; and the Education Register (UDDA) that has the highest achieved education. All these files are matched using individual and firm-level identifiers.

Due to the availability of occupation codes, we restrict the analysis periods between 1993 and 2022. Our sample is a population aged 25-64 with non-missing highest achieved education codes, residential municipality, and age (98.5% of the individual-year pairs).

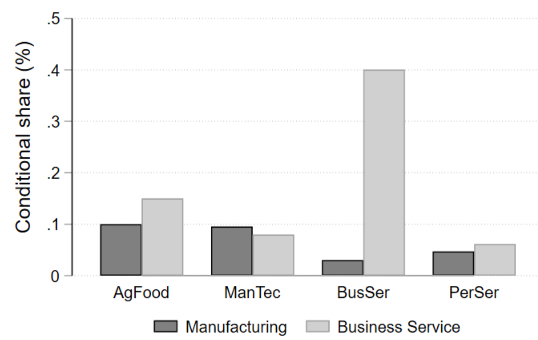
Figure 1 shows the basic facts of program participation shares. Panel 1a shows the portfolio of manufacturing and BS programs experiences, which is defined by the cumulative experiences of individuals at each age if they have taken, since age 25, (i) none of the programs, (ii) only the manufacturing programs, (iii) only the BS programs, or (iv) both of the manufacturing and BS programs. We find that the cumulative experience increases throughout the life cycle, at least until around the mid-40s, that BS programs are more popular than manufacturing programs, and most individuals take courses in at most one area through the life cycle. Panel 1b shows the share of individuals who take manufacturing and BS programs, conditional on the current occupations they work at. We confirm that BS programs are taken by more workers in general. We also find that there is a positive correlation between the current occupation group and the apprenticeship program category–For manufacturing occupation workers, the manufacturing program share is larger than the BS program share; for BS occupation workers, BS programs dominate the program take-up.

Figure 1: Basic Facts about the Adult Apprenticeship

(a) Portfolio



(b) Conditional Share of Program Take-up



Note: The left panel shows the “portfolio” of manufacturing and business-service (BS) program experiences. The portfolio is the cumulative experiences of individuals at each age if they have taken, since age 25, (i) none of the programs (not shown in the diagram), (ii) only the manufacturing programs (solid line), (iii) only the BS programs (long dash line), or (iv) both of the manufacturing and BS programs (short dash line). The right panel shows the conditional share of individuals who take manufacturing (dark grey) and BS programs (light grey), depending on their current occupations. “AgFood” stands for the Agriculture and Food (FJO) occupations, “ManTec” for Manufacturing and Technology (TBT) occupations, “BusSer” for Business service (KHF) occupations, and “PerSer” for Personal Service (OSP) occupations.

3 Empirical Analysis

We study the observed dynamic relationship between education program and occupation take-up using local-project difference-in-difference and the relationship between earnings and past program take-up by a modified Mincer regression.

3.1 Empirical Strategy

Training Program and Occupation Choice. To study the dynamic effect of adult apprenticeship programs, we begin by constructing treatment and comparison groups. For this purpose, denote τ as a treatment year, o as an origin occupation group, and v as an education program category. We then match individuals in the following two steps. First, for each (τ, o), we select all individuals that worked in occupation o in all years $t = \tau - 5, \ldots, \tau - 1$. This step ensures that the work history five years prior to the treatment is matched between the treatment and comparison groups, following the literature that it is critical to consider a work history in the matching procedure as it is a crucial factor that reflects individual unobserved heterogeneity (Jespersen et al., 2008). Second, for each v, we define a treatment group as individuals who take up education in category v for the first time in year τ, and a comparison group as those who did not take up a course in area v in year τ.

For each (o, v, τ), we estimate the following local-projection (LP) difference-in-difference specification:

$$y^{v}_{i,t+k} - y^{v}_{i,t-1} = \alpha^{o,v,\tau}_{jt} + \beta^{o,v,\tau}_{k} \Delta D^{v}_{it} + \sum_{p=0}^{P} \left(\Delta X_{i,t-p}\right)' \gamma^{o,v,\tau}_{p,k} + \varepsilon^{o,v,\tau}_{i,t,k}, \tag{1}$$

where $k = -4, \ldots, 8$ with $k \neq -1$ is the lag and lead from the treatment, y^{v}_{it} is the indicator for employment in occupation v, $\alpha^{s,v,\tau}_{jt}$ is the "group"-j and year-t specific fixed effects, D^{v}_{it} is the indicator for the category-v course take-up by year t (so that $D^{v}_{it} = 1$ is an absorbing state), and $X_{i,t-p}$ is a control variable vector with lags $p = 0, \ldots P$. For group j, we use a 6 digit-industry and non-employed indicator. For control variables, we use the indicator of positive yearly earnings and log of earnings plus one. The parameter of interest is $\beta^{s,v,\tau}_{k}$ that measures the probability change of working in category v between 1 year before and k years after the course by course takers for the (o, v, τ) group of treatment and control.

We also estimate an aggregated dynamic treatment effect for each origin occupation o and education category v by stacking samples across τ. In this case, the treatment is staggered in the stacked sample, and thus, we need to make sure that the "negative weight" problem in the literature of staggered and dynamic treatment effect estimation.[4] Following the strategy proposed by Dube et al. (2022), we define an unclean control indicator $UC_{i,t,k}$ that equals zero if $\Delta D_{it}^{v} = 1$ or $\Delta D_{i,t+h}^{v} = 0$ for $h \leq k$ and one otherwise. This is equivalent to defining the observation (i,t) as a "clean" unit if either it is treated in period t or it did not receive any treatment up to year $t+k$, and including $UC_{i,t,k}$ eliminates the negative weight problem due to including previously treated units in the comparison group. Formally, we estimate

$$\begin{aligned} y_{i,t+k}^{v} - y_{i,t-1}^{v} =& \alpha_{jt}^{s,v}\left(1+\phi_{jt}^{s,v}UC_{i,t,k}\right) + \beta_{k}^{s,v}\Delta D_{it}^{v} + \theta_{k}^{s,v}UC_{i,t,k} \\ &+ \sum_{p=0}^{P}\left(\left(1+\rho^{s,v}UC_{i,t,k}\right)\Delta X_{i,t-p}\right)'\gamma_{p,k}^{s,v} + \varepsilon_{i,t,k}^{s,v}. \end{aligned} \tag{2}$$

The parameter of interest is $\beta_{k}^{s,v}$, which represents a weighted average of cohort-specific treatment effects with positive weights that reflect treatment variance and subsample size.

The identification assumption in the LP-DiD is that conditional on the work history, control variables, and fixed effects, program take-up is exogenous to the error terms. In a meta-analysis study, Card et al. (2018) report that the average program effects based on randomized experiments are similar to those from non-experimental designs. While it is still a stringent assumption, we will not derive any conclusive insights from the reduced-form analysis but leave the policy-relevant discussions in the structural analysis.

Modified Mincer Equation. To study the role of program participation on earnings, we estimate the following Mincer equation modified to the adult apprenticeship setting: for

[4]Multiple papers, including De Chaisemartin and d'Haultfoeuille (2020), point out and propose a correction method to this problem. We prefer the LP approach to the two-way fixed-effect (TWFE) approach for two reasons. First, the LP approach uses a first-difference equation and does not require to include the individual fixed effect in the right-hand side, which is computationally less demanding. Second, the LP estimator for $\beta_{k}^{s,v,\tau}$ does not depend on the choice of the window period for k since equation 1 does not depend on other values of k, while the TWFE estimator does.

each occupation group o,

$$\ln earnings^{o}_{i,t} = \beta^{o}_{0} + \beta^{o}_{1} age_{i,t} + \beta^{o}_{2} \left(age_{i,t}\right)^{2} + \beta^{o}_{3} tenure^{o}_{i,t} + \beta^{o}_{4} training^{o}_{i,t} + \eta^{o}_{i} + \varsigma^{o}_{i,t}, \text{ if } o_{it} = o, \tag{3}$$

where log earnings are regressed on age and its square (potential experiences) and occupation-specific tenures (consecutive years of work, measuring the actual experience), as in a standard Mincer equation, and η^{o}_{i} is the individual fixed effect. Furthermore, we include a term of $training^{o}_{i,t}$, which is the indicator variable if the individual has taken a program in the program field that is relevant to occupation o. Therefore, β^{o}_{4} captures how many percent current earnings are correlated with past training, conditioning other Mincer variables and fixed effects.

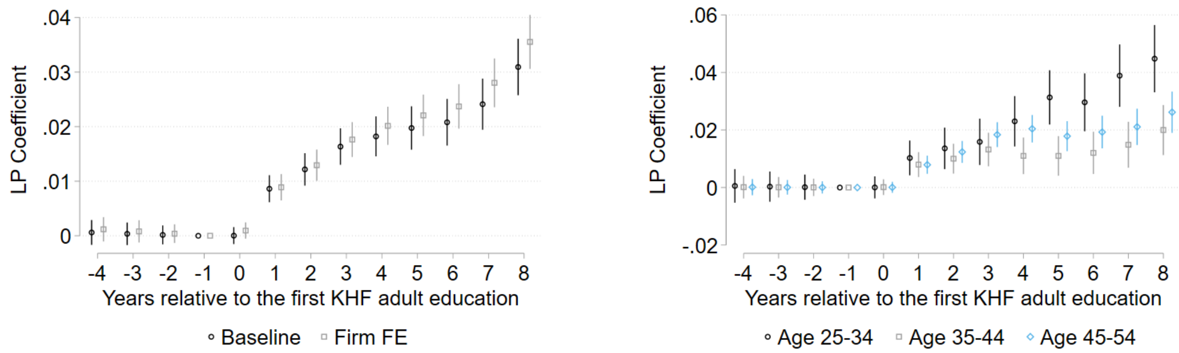
3.2 Results

We report estimation results of our aggregated LP specification (2) for the past occupation o being manufacturing and education program category v being BS in Figure 2, and relegate other results to the Appendix. Panel 2a is the baseline result, which shows that there are no pre-trends before the program take-up, and those who take up BS programs tend to move to BS occupations with 0.9-3.1 percentage point higher in 1-8 years after the program than those who did not. Therefore, BS programs are likely to play a role in helping those who have been in manufacturing occupations to move towards BS occupations. This finding is consistent with Kambourov et al. (2020), who showed government sponsored training tends to shift workers into different occupations.

Figure 2: Local-projection Difference-in-difference Estimates

(a) Baseline Result

(b) Subsample Analysis By Ages



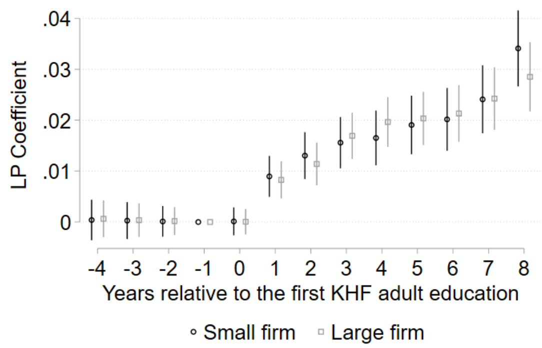
Note: The local projection difference-in-difference estimates from (2), where the past occupation o is the manufacturing occupation and education category v is business service, defined in Table 1. The left panel shows the baseline result (circle marker) and the result with firm fixed effects (square marker). The right panel shows the results with the subsample analysis across different age groups. Error bars show 95 percent confidence intervals. Standard errors are clustered at the individual and industry-year levels.

Panel 2a also shows the results of the same specification with the firm fixed effect, and they are qualitatively similar to the baseline. Therefore, workers move occupations, whether or not the transitions involve changes in firms or not. This is consistent with the relatively minor role played by firms in the context of adult apprenticeship, but the program take-up decision and occupation switches are driven primarily by individual workers. This point can also be confirmed in Figure 3a, where we verify our baseline results are robust to the subsample analysis by different firm sizes.

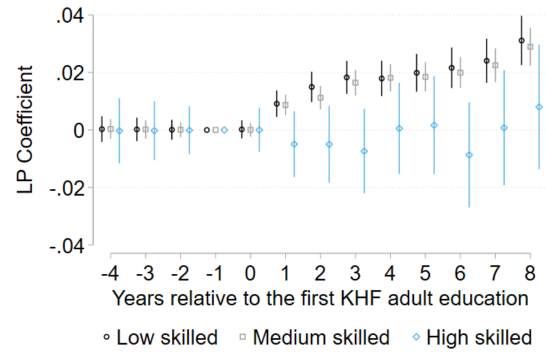
To explore the source of the positive effect of switching from manufacturing and BS occupations, we explore the analysis across subsamples in Panel 2b and Figure 3. First, we find that the effect is found across all age groups, but the point estimates are larger for the youngest group of individuals (aged 25-34). This is consistent with the life-cycle model and human capital accumulation, as the value of switching to a new occupation is higher for young individuals than for older ones. In Panel 3a, we also find that the effects are similar across firm sizes, which mitigates the role of within-firm job assignment that is especially prevalent for large Danish firms (Frederiksen and Kato, 2018). The effects are also similar between graduates of general upper secondary education and vocational

Figure 3: Subsample Estimates for the Local-projection Difference-in-difference Specification

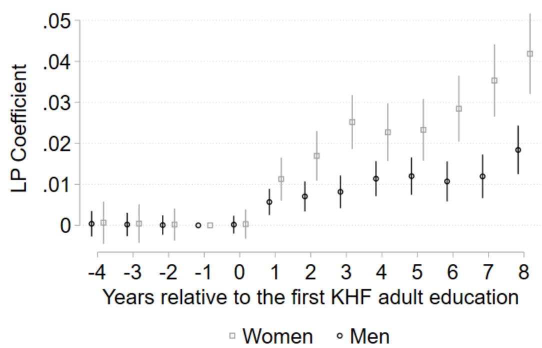
(a) Across Firm Size



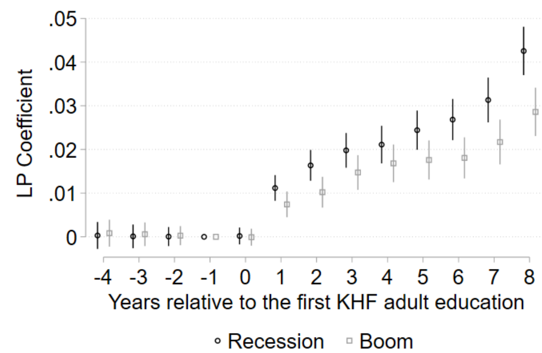
(b) Across Education Level



(c) Across Gender



(d) Across Business Cycle



Note: The subsample estimates for the local projection difference-in-difference estimates from (2), where the past occupation o is the manufacturing occupation and education category v is business service, defined in Table 1. The left top panel shows the results with the subsample across different firm sizes ("Small firm" being below the median; "Large firm" being above the median). The right top panel shows the results with the subsample across different education levels ("Low skilled" being less than high school graduates; "Medium skilled" being youth vocational education; "High skilled" being more than college). The left bottom panel shows the results with the subsample across gender. The right bottom panel shows the results with the subsample across the business cycle, where the recession period is defined by the OECD Recession Indicators for Denmark from the Peak through the Trough taken from the FRED website. Error bars show 95 percent confidence intervals. Standard errors are clustered at the individual and industry-year levels.

education, while we cannot detect significant effects for high-skill individuals with more than college education (Panel 3b). As Card et al. (2018) point out, in general, the effect of the ALMP depends on gender and business cycle. Consistent with their findings, the effects for women are larger than for men, while they are positively significant for both genders (Panel 3c). Furthermore, the difference of the effects during the recession and boom periods is similar (Panel 3d).

In Appendix Figure A.1, we show the results for the other combination of past occupation and programs (o, v). Although there is no pretrend detected before the treatment in all combinations, we find positive and significant dynamic treatment effects of apprenticeship programs if and only if v is BS. For the case of o being BS, this suggests a positive effect of *upskilling* since treated workers receive education on similar skills as those that are used in their previous jobs. By contrast, main results in Figure 2a can be seen as *reskilling* in BS occupations since treated workers receive education about different skills from those used in their previous jobs. Appendix Figure A.2 shows the result with the outcome variable of overall (instead of occupational) employment, confirming positive effects for BS education (and manufacturing education for some groups) without any significant pre-trends. Finally, in Appendix A.2, we show the results of cohort-specific estimation in equation (1).

Turning to the modified Mincer equation, Table (2) shows the regression results. Consistent with the literature, we find positive and significant tenure effects on earnings–One additional year of the experience in occupation increases the earnings by 1.2-1.7 percent, depending on occupations. Moreover, we find evidence of the positive association between past training take-up and current earnings in manufacturing and BS occupations. The coefficient is even larger than the tenure effect, having a 2-3 percent effect on earnings if an individual has taken a program in the relevant field. We could not find conclusive evidence for occupations in agriculture/food and personal services possibly because of the lack of enough variation or the negative bias due to the short-term wage drop after occupation switches as argued in Kambourov et al. (2020). These results suggest that apprenticeship training positively affects on human capital development in manufacturing and BS occupations.[5]

Furthermore, the Appendix shows a version of (3) with the time fixed effect as our

[5] Although we cannot completely disregard the possibility that the positive coefficient is an artifact of labor market signaling rather than the human capital accumulation (Spence, 1978), we believe this concern is minor given the target of the adult apprenticeship is at low-skilled adults.

Table 2: Modified Mincer Equation Estimates

	log earnings			
	AgFood.	Manuf.	BusSer.	PerSer.
Tenure	0.0134***	0.0120***	0.0157***	0.0173***
	(0.0009)	(0.0001)	(0.0001)	(0.0001)
Training	-0.0456	0.0338***	0.0247***	-0.0473*
	(0.0674)	(0.0071)	(0.0029)	(0.0189)
Age controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
N	148611	6152134	4133980	6591667

Note: Estimation results of the modified Mincer equation (3) is shown. "AgFood" stands for the Agriculture and Food (FJO) occupations, "ManTec" for Manufacturing and Technology (TBT) occupations, "BusSer" for Business service (KHF) occupations, and "PerSer" for Personal Service (OSP) occupations. Standard errors are clustered at the individual and industry-year levels and shown in parentheses.

motivation is structural change and labor market shocks, which are timely events (Table A.5). To deal with a concern about earnings mean reversion, we also perform a robustness exercise with an additional control variable of lagged outcome variable (log earnings, Table A.6). Results are robust to these extensions.

Overall, we have shown positive correlations between adult apprenticeship program take-up, occupation choice, and earnings. However, these results are based on arguable identification assumptions on program selections. Furthermore, these empirical results are insufficient to rigorously sort out the job transition mechanisms and quantitatively analyze hypothetical policy reforms on apprenticeship programs. To overcome these shortcomings, we will develop a structural model and discuss individual joint decisions of occupations and education programs and the effect of wage subsidy reforms in the next section.

4 Model

We consider an individual life-cycle model with a discrete choice of participation in apprenticeship programs as well as jobs. We choose a partial equilibrium framework to keep the model simple, motivated by the fact that the take-up rate of any adult apprenticeship programs over the life-cycle is fairly low, indicating that the general equilibrium forces (e.g., reactions in skill and goods prices) due to the change in adult apprenticeship program is likely to be limited.

4.1 Environment

Time is discrete. Consider an individual i who enters at time $t = 0$ and exits at $t = T$, which we occasionally refer to as age as we consider an individual's problem. Individual heterogeneity is denoted by ω, and its specification will be introduced later. There are occupations $o \in 0 \cup \mathcal{O}$ and apprenticeship program $v \in 0 \cup \mathcal{V}$, where $o = 0$ means not employed and $v = 0$ means not in any program. Guided by the above empirical analysis, we set $\mathcal{O} = \mathcal{V}$, and denote the element of these sets by $1, \ldots, O$.

The timeline of the individual decision making is the following. At the beginning of each period t, an individual draws a vector of occupation o-program v-specific idiosyncratic preference shock $\boldsymbol{\epsilon}_t \equiv \{\epsilon_{o,v,t}\}_{o,v}$. Given the realized value of $\boldsymbol{\epsilon}_t$, she chooses the occupation and program (o, v), gets and consumes the earnings. Formally, the lifetime utility maximization problem in year $t \in [0, T]$ is

$$V_t = \max_{\left\{o_{t'}, v_{t'}\right\}_{t'=t}^{T}} E_t \sum_{t'=t} \beta^{t'-t} \left(U^D_{o_{t'}, v_{t'}, t'} + \epsilon_{o_{t'}, v_{t'}, t'} \right),$$

where $U^D_{o_t, v_t, t}$ is the deterministic utility component that depends on if the individual is working or not, and E_t is the expectation conditional on the information set at the beginning of period t, $\beta \in (0, 1)$ is the discount factor. If the individual works, the per-period utility is given by $U_{o_t, v_t, t} = w_{o_t, v_t, t} h_{o_t, t}$, where $w_{o,v,t}$ is the market wage in occupation o

when taking program v in year t, and $h_{o,t}$ is the occupation o-specific human capital level (e.g., Kambourov and Manovskii, 2009). The market wage $w_{o,v,t}$ depends on the program to incorporate the wage subsidy of taking the program, over which we will perform counterfactual analysis.

We assume that the preference shock $\epsilon_{o,v,t}$ follows correlated Gumbel distribution with the following set of parameters. The scale parameter σ governs the elasticity of occupation choice as in Traiberman (2019). Next, the correlation parameter ρ_o governs the elasticity of program choice conditional on working in occupation o. We allow a flexibility where this sensitivity can depend on the current employment and occupation status. Finally, the distribution also depends on location parameters $A_{o,v}$, which governs the average share of individuals taking (o, v).

For each occupation o, the human capital level is determined by

$$\ln h_{o,t} = \beta_0^o + \beta_1^o t + \beta_2^o t^2 + \beta_3^o ten_{o,t} + \beta_4^o training_{o,t} + \omega_o + \varsigma_{o,t} \tag{4}$$

where $ten_{o,t}$ is the tenure of working in occupation o, $training_{o,t}$ is the take-up status of program in occupation o in year $t-1$, and $\varsigma_{o,t}$ is a error term following a normal distribution. In the same spirit as Traiberman (2019), we assume that $\varsigma_{o,t}$ is unknown at the time of (o_t, v_t) decisions, and that human capital is non-transferable across occupations. Namely,

$$ten_{o,t} = \begin{cases} ten_{o,t-1} + 1 & \text{if } o_t = o_{t-1} \\ 0 & \text{otherwise} \end{cases}. \tag{5}$$

Non-employment is voluntary and per-period utility is given by an age-dependent function

$$U_{0,t}^D = \beta_0^0 + \beta_1^0 t + \beta_2^0 t^2 + \omega_0,$$

independent of tenure or past training.

4.2 Solution

To solve the model, we introduce the Bellman representation. We use "tilde" notation to denote variables determined at the beginning of each period, so the state variables. In this model, the state space is previous tenure, occupation, program, and individual type, $\tilde{s} = (\tilde{ten}, \tilde{o}, \tilde{v}, \omega)$. With these notations, we can write the deterministic choice-specific value function V_t^D as

$$V_t^D (o, v|\tilde{s}) = w_{o,t} h_t (o, v|\tilde{s}) + \beta E_t V_{t+1} (s (\tilde{s}, o, v)),$$

for any t, where $s (\tilde{s}, o, v) = (ten (o|\tilde{s}), o, v, \omega)$, $ten (o|\tilde{s})$ is the current period tenure variable conditional on $\tilde{s}$ determined by (5), and $E_t V_{t+1} (s (\tilde{s}))$ is the expected ex-ante expected value function conditional on the state variables, satisfying the terminal condition $V_{T+1} = 0$. The optimization problem is then equivalent to solving $\max_{(o,v)} V_t^D (o, v|\tilde{s})$, and the solution can be characterized by (o, v)-specific choice probability $\pi_t (o, v|\tilde{s})$. We also use notations of conditional choice probability of education v, $\pi_t^C (v|o, \tilde{s})$, marginal choice probability of $\pi_t^M (o|\tilde{s})$, satisfying

$$\pi_t (o, v|\tilde{s}) = \pi_t^C (v|o, \tilde{s}) \pi_t^M (o|\tilde{s}). \tag{6}$$

Using the correlated Gumbel distribution, we can show that the ex-ante value function has a closed form

$$V_t (\tilde{s}) = \sum_{o,v} \left(\exp \left(\frac{1}{\sigma (1 - \rho_o)} \left(V_t^D (o, v|\tilde{s}) + A_{o,v} \right) \right) \right) \tag{7}$$

up to the Euler-Mascheroni constant. The marginal choice probability of occupation o is given by

$$\pi_t^M (o|\tilde{s}) = \frac{\sum_v \exp \left(\frac{1}{\sigma} \frac{V_t^D(o,v|\tilde{s}) + A_{o,v}}{1-\rho_o} \right)}{\sum_o \sum_v \left(\exp \left(\frac{1}{\sigma} \frac{V_t^D(o,v|\tilde{s}) + A_{o,v}}{(1-\rho_o)} \right) \right)}, \tag{8}$$

as in Traiberman (2019), so the larger $1/\sigma$, the more sensitive $\pi_t^M (o|\tilde{s})$ is to the choice-specific value function. Moreover, the program v choice probability conditional on the current occupation o is

$$\pi_t^C\left(v|o,\tilde{s}\right)=\frac{\exp\left(\frac{1}{1-\rho_o}\left(V_t^D\left(o,v|\tilde{s}\right)+A_{o,v}\right)\right)}{\sum_v\exp\left(\frac{1}{1-\rho_o}\left(V_t^D\left(o,v|\tilde{s}\right)+A_{o,v}\right)\right)}. \tag{9}$$

Here, the sensitivity of the choice probability depends on o, and as $1/\left(1-\rho_o\right)$ is large, $\pi_t^C\left(v|o,\tilde{s}\right)$ is sensitive to the choice-v specific value function with choosing occupation o. With expressions (8) and (9) in hand, we can solve the joint probability by (6).

4.3 Discussions

We discuss issues arising from our model assumptions.

The Relation between Occupations and Skills. In our model, vocational skills are simplified and have a one-to-one relationship with the occupation group, so that $\mathcal{O}=\mathcal{V}$. By contrast, several past studies explore different specifications. Examples include task-specific skills in Gathmann and Schönberg (2010) and job-specific mix of general multi-dimensional skills in Lazear (2009) and Cavounidis and Lang (2020). These works provide a parsimonious way to describe the set of potentially multi-dimensional skills required by labor demand, be it occupations or firms. In relation to these studies, our model setting can be regarded as a special case in which each occupation demands only one of the occupation skills but not skills in other occupations. We believe that this setting is natural in our application of vocational training as skills are fairly horizontally differentiated, although extending it to the one with multi-dimensional requirements of skills by each occupation has the potential to provide different interpretations of vocational skills.

On the Renewal Action Assumption (5). This assumption implies the renewal action being the occupation switch in the dynamic discrete choice literature (Arcidiacono and Miller, 2011). Although it is restrictive, it is widely used as it helps to reduce the state space and helps develop an estimation equation. It is possible to relax the assumption by letting the renewal action be, for example, only the not employed (but not the occupation switch) or away from the previous occupation for more than two periods, with a reasonable increase in computation time.

The Implication of the Correlated Gumbel Distribution. The correlated Gumbel distribution implies an education take-up and occupation switch decisions in a similar manner as the nested CES, with the upper nest being the occupation choice and the lower nest the program take-up decision. As such, the dependence of ρ_o on occupation o captures the heterogeneous sensitivity of education take-up decision to the change in the expected value of taking up a program relative to that of not taking up across occupations. Therefore, for example, we can allow that the workers' sensitivity is lower when not working than when working due to reasons outside of the model (e.g., lack of information when not working).

The correlated Gumbel distribution we adopt has a key restriction: any shocks in other occupations do not affect the probability of education take-up decision in the current occupation, conditional on working in one occupation. A possible model choice to avoid this would have been to reorder the upper and lower nests and assume the program v-conditional elasticity of occupation-o substitution. A benefit of such an approach is that we can allow the occupation switch sensitivity to differ across different education take-ups. However, this approach may be tricky when it comes to estimation since we would need to either use a small sample of education takers to infer the flexible and key elasticity parameters or to keep track of all the past education take-ups.

5 Estimation

5.1 Estimation Method

We implement a three-step estimation, extending Traiberman (2019). First, we estimate the human capital function with finite dependence. Second, we estimate the job choice sensitivity parameter σ using the Bellman equation (Artuç et al., 2010). Finally, we estimate the program choice sensitivity parameter ρ_o using a similar idea as the second step.

To implement the first step, we construct the joint likelihood for individual i in year t, conditional on individual heterogeneity ω as $l_{it|\omega} = l(w_{it}, s_{i,t}, s_{i,t-1}|\omega_i, t)$. Using the assumption that wage error ς is not observed at the time of occupation and program choice, we can write it as

$$l_{it|\omega} = \varphi\left(\ln w_{it}|s_{i,t}, \omega_i, t\right) \pi_t\left(s_{i,t}|s_{i,t-1}, \omega_i\right), \tag{10}$$

where φ is the normal density function and To specify the full likelihood function implement the maximum likelihood (ML), we can perform the pseudo-expectation-maximization (EM) algorithm developed by Arcidiacono and Miller (2011), using the empirical distribution of choice probabilities instead of the model solution π_t. However, in this version, we simplify estimation by shutting down individual heterogeneity ω. In this case, the use of the empirical choice probability is simply substituting π_t in (10) with the observed ones, and the ML simply maximizes the likelihood component of human capital. Therefore, our first step is equivalent to the occupation-specific Mincer regression that is already shown in Table 2. This has a strong restriction on the selection of programs, and will be relaxed in a future version.

We then discuss how to estimate the second and third step. To do so, we use the closed-form value function (7) and choice probabilities (6), (8), and (9), to get

$$V_t\left(\tilde{s}\right) = \sigma\gamma + A_{o,v} + w_{o,t}h_t\left(o|\tilde{s}\right) - \sigma\ln\left(\pi_t\left(o,v|\tilde{s}\right)\right) + \beta E_t V_{t+1}\left(s\left(\tilde{s},o,v\right)\right), \tag{11}$$

where γ is the Euler constant. The intuition for this expression is that, conditional on earnings $w_{o,t}h_t\left(o|\tilde{s}\right)$ and expected discounted future value $\beta E_t V_{t+1}\left(s\left(\tilde{s}\right)\right)$, the remaining variation in the choice probability $\pi_t(o, v|\tilde{s})$ is in the denominator. Thus, the likelier (o, v) is chosen at t (so the higher $\pi_t(o, v|\tilde{s})$), the lower the ex-ante value function $V_t(\tilde{s})$, the denominator of the choice probability. This expression is useful to derive the estimation equation based on observable objects such as $w_{o,t} h_t(o|\tilde{s})$ and $\pi_t(o, v|\tilde{s})$, given that we can condition on unobservable value functions $V_t(\tilde{s})$ and $E_t V_{t+1}(s(\tilde{s}))$.

To control for the past values $V_t(\tilde{s})$, we simply take two different (o, v) paths that start from the same state variable $\tilde{s}$. To control for the future expected values $E_t V_{t+1}$, we extend the path by one period ahead and use notation o' to denote it. Note that the model restriction implies:

$$ten\left(o'|ten\left(o|\tilde{ten}, \tilde{o}\right), o\right) = ten\left(o'|ten\left(\tilde{o}|\tilde{ten}, \tilde{o}\right), \tilde{o}\right) = 0, \ \forall o' \neq o, \tilde{o}$$

due to the renewal action assumption (Traiberman, 2019). Namely, no matter what the current choice of occupation o is, the next period tenure to work in a different occupation $o' \neq o$ must be zero. To operationalize this restriction, we iterate (11) one period and rearrange it to have

$$\begin{aligned}
&\ln\left(\frac{\pi_t(o, v|\tilde{s})}{\pi_t(\tilde{o}, \tilde{v}|\tilde{s})}\right) + \beta \ln\left(\frac{\pi_{t+1}(o', v'|s(\tilde{s}, o, v))}{\pi_{t+1}(o', v'|s(\tilde{s}, \tilde{o}, \tilde{v}))}\right) \\
&= c + \frac{1}{\sigma}\left(w_{o,t} h_t(o|\tilde{s}) - w_{\tilde{o},t} h_t(\tilde{o}|\tilde{s})\right) + \left(A_{o,v} - A_{\tilde{o},\tilde{v}}\right) + \mu_{t+1}\left(o', v', o, v|\tilde{s}\right)
\end{aligned}$$

for any $\tilde{s}$, where c is a constant and μ_{t+1} is the forecast error satisfying $E_t \mu_{t+1} = 0$. With the first-step estimates on the human capital function, all variables are observed and the equation can be estimated with least squares with fixed effects, where the coefficient on the wage differential identifies the job choice sensitivity parameter $1/\sigma$, and the fixed effects identify location parameters $A_{o,v}$.

Applying the similar idea, we can estimate the program choice sensitivity parameter $1/(1 - \rho_o)$ since conditioning on the current occupation o helps control for the tenure evolution, and estimates on σ and $A_{o,v}$ can be used to measure the choice-specific value function. Specifically, we take two programs v_1 and v_0 that are different from the current occupation o, and can show

$$\ln\left(\frac{\pi_t^C\left(v_1|o,\tilde{s}\right)}{\pi_t^C\left(v_0|o,\tilde{s}\right)}\right)=\frac{1}{1-\rho_o}\left(V_t^D\left(o,v_1|\tilde{s}\right)-V_t^D\left(o,v_0|\tilde{s}\right)\right)+\mu_{t+1}^{educ}\left(o,v_1,v_0|\tilde{s}\right) \tag{12}$$

for any o and $\tilde{s}$, where $V_t^D\left(o,v_1|\tilde{s}\right)-V_t^D\left(o,v_0|\tilde{s}\right)$ is the relative value of choosing v_1 to v_0, satisfying

$$V_t^D\left(o,v_1|\tilde{s}\right)-V_t^D\left(o,v_0|\tilde{s}\right)=\frac{A_{o,v_1}-A_{o,v_0}}{\sigma}-\beta\ln\left(\frac{\pi_{t+1}\left(o',v'|s\left(\tilde{s},o,v_1\right)\right)}{\pi_{t+1}\left(o',v'|s\left(\tilde{s},o,v_0\right)\right)}\right)$$

for any o' and v', and μ_{t+1}^{educ} is the forecast error satisfying $E_t\mu_{t+1}^{educ}=0$.

5.2 Results

Table 3 shows the estimates of location parameters, averaged across different programs and occupations, respectively. Therefore, column A^O shows the average occupation-specific location parameters, while A^V shows the average program-specific location parameters, normalized to the average location parameter for not employed, which is zero. We find that the occupation-specific location parameters are all negative, implying the disutility of working relative to not working. Next, the program-specific location parameters are negative and large in absolute terms for all four program groups, while the parameter is positive for the no-program take-up. These imply a stronger reluctance to participate in the program than to work, as depicted in Figure 1a.

We estimate the scale parameter at $1/\sigma = 1.11$, with a standard error of 0.09. This value is close to the estimates in Traiberman (2019), whose preferred value is $1/\sigma = 1.43$ with a standard error of 0.05. Samples used in these two studies are taken from Danish administrative data, but our data construction differs since we merge the education register and focus on the population where adult apprenticeship is relevant, and our model adds education choice. We still find a qualitatively similar value for the occupation choice sensitivity, which confirms the robustness of the past study.

Table 3: Average Location Parameter Estimates

Occupation/programs	A^O	A^V
Agriculture and Food	-1.00	-2.67
Manufacturing and Technology	-0.81	-1.26
Business Service (BS)	-0.93	-1.44
Personal Service (PS)	-0.75	-2.00
No education	-	1.26

Note: The table shows the averages of the estimates of location parameters. A^O stands for the location parameters averaged for each occupation choice o, while A^V stands for the location parameters averaged for each program choice o. The parameter is normalized so that $A^O = 0$ for not employed, and that value is suppressed in the table.

Table 4: Estimates of Program Takeup Sensitivity

Occupation	(1) Not employed	(2) Food	(3) Manu	(4) BS	(5) PS
$1/(1-\rho_o)$	0.490***	0.829***	0.924***	0.809***	0.938***
	(0.0205)	(0.0082)	(0.0046)	(0.0051)	(0.0044)
N	4896	12078	21945	17964	22425
R-squared	0.104	0.457	0.633	0.587	0.666

Note: The table shows the estimates of program take-up sensitivity or the correlation parameter in the correlated Gumbel distribution, estimated as the slope coefficient of regression (12). In each column, estimates for different occupation groups o are shown: Column (1) shows one for individuals not employed, (2) for workers in agriculture and food occupations, (3) for those in manufacturing and technology occupations, (4) for those in business service occupations, and (5) for those in personal service occupations. Standard errors are clustered at the level of the state variable $\tilde{s}$ in (12) and shown in parentheses. *** p<0.01.

Table 4 shows the estimates of education choice sensitivity $1/(1-\rho_o)$ for different occupation groups o. First, we find that education program choice elasticity is smaller than occupation choice elasticity $1/\sigma$. This reveals a general insensitivity of individuals to choose programs when the value of doing so varies. Second, the estimate is particularly small for those not currently employed, suggesting a special insensitivity for this group of people. This special insensitivity could be due to the limited information about program availability when not working, while we do not take a strong stance on the exact cause of the parameter estimates.

To check if our estimated model fits well with the observed variation, we fit the con-

Table 5: Model Fit

	Joint (o, v)	Marginal (o)	Marginal (v)
Simulated share	2.047***	1.222***	1.505***
	(0.00628)	(0.00405)	(0.00518)
N	98,058	34,641	44,509
R-squared	0.520	0.724	0.655

Note: The regression result of observed choice probability on model-implied choice probability $\pi_t(o, v|\tilde{s})$. Each observation is possible combinations of $(o, v, \tilde{s}, t)$. The first column shows the result of (o, v)-joint distribution, the second column that of o-marginal distribution (Hence $\pi^M(o|\tilde{s})$ in eq. 8), and the third column that of v-marginal distribution. Standard errors are clustered at the $(\tilde{s}, t)$ level and shown in parentheses. *** p<0.01.

ditional choice probabilities $\pi_t(o, v|\tilde{s})$ from data and model for each $o, v, \tilde{s}$, and t. Table 5 shows the result of this exercise. We find that our model can explain more than half of the data variations based on the R-squared measures for both joint and marginal distributions.

6 Counterfactual Exercise

In this section, we demonstrate that our framework can be useful for several policy counterfactuals. There have been several changes in the wage subsidies of adult education programs in Denmark, while no evaluation of such policy changes with regard to life-cycle labor supply has been made, partly due to the lack of an appropriate theoretical framework. Our stylized model provides a first look at this issue.

Specifically, we consider a permanent 10% increase in the wage rate $w_{o,v,t}$ conditional on taking apprenticeship programs. This exercise can be thought of as an increase in the wage subsidy reform,[6] or reducing the opportunity cost due to the time spent on programs (without sacrificing the program effects). We evaluate two scenarios, one where the subsidy is only conditional on taking programs, without specifying the types of the

[6]The wage subsidy was initially as low as about 5 USD per hour and was gradually raised to 10 USD in nominal terms (Deloitte, 2013). The 10% subsidy increase roughly amounts to this increase for the average earnings individual in real terms.

programs ("universal exercise"), and the other where the subsidy is targeted at business service (BS), so given only to those who take up programs in the BS category ("BS-targeted exercise").

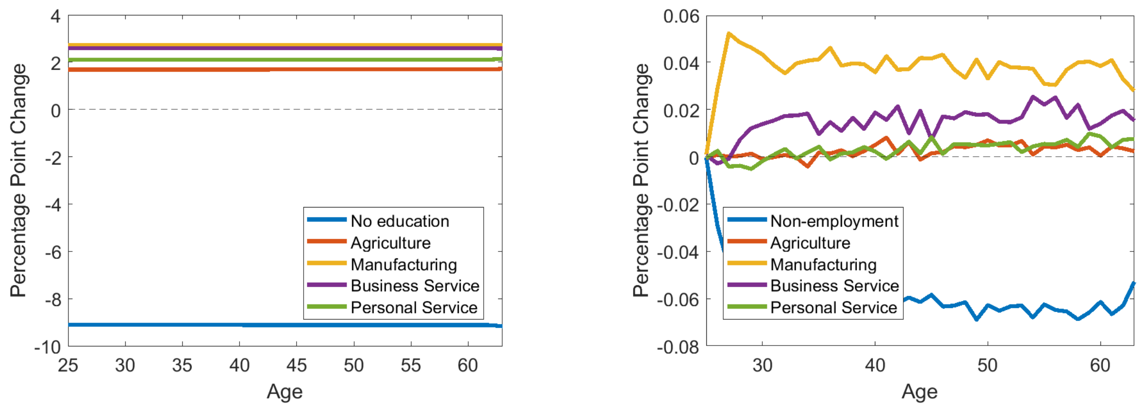
We consider a hypothetical individual from age 25 and examine the impact on the conditional choice probabilities over the life cycle and average earnings. To compute such probabilities and averages, we simulate 100,000 individuals and compute the full life-cycle path of the state vector $\tilde{s}$, based on the model solution (8) and (9).

The effect of the universal exercise on choice probabilities is shown in Figure 4. From the left panel, we confirm that the individual is likely to shift from non-education in the baseline to some education take-up throughout the life-cycle, as predicted from the model. Moving on to the right panel, we find that the share of individuals increased for manufacturing occupations the most, followed by BS occupations. There is almost null effect on the share of food/agriculture and personal service occupations, and the not-employed category absorbs all the reduction in the share. This effect size order among the four employment category aligns with the baseline employment share. Therefore, the universal exercise expanded the employment share gap between occupations. The primary reason is the complementarity between the tenure and program take-up effect in developing human capital and wages. It is more beneficial for workers in traditional occupations with large shares of employment, in which they accumulate human capital by tenure anyway, to take up the programs in the relevant fields. This can be confirmed by a relatively large increase in the take-up of manufacturing and BS programs in the left panel.

Turning to the BS-targeted exercise, we show the result in Figure 5. From the left panel, we confirm a shift from all other education categories to BS education throughout the life-cycle, as predicted from the model. In the right panel, we find that the occupation choice probability increased significantly for BS occupations. Strikingly, there is a strong churning effect, with the employment share of manufacturing occupations dropping significantly. The main reason is the substitution of human capital development by

Figure 4: The Effect of Universal Exercise on Program and Occupation Choice Probabilities

(a) Education takeup (b) Occupation choice



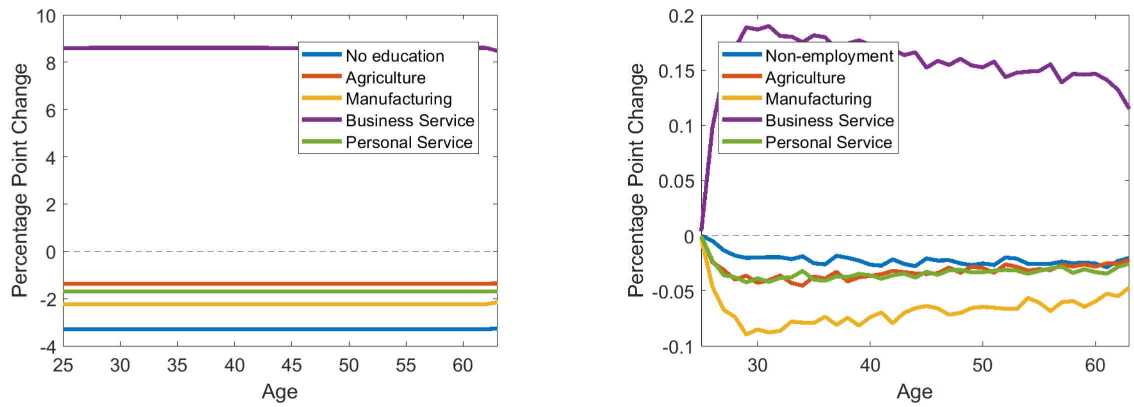
Note: Figures show the effect of the universal exercise, where a 10% wage subsidy is given to those who take up any programs, on individuals' apprenticeship program and occupation choice probabilities. The left panel shows the effect on the choice probability of program take-up, while the right panel shows the impact on the occupation choice probabilities.

formal apprenticeship programs rather than experience in the work. In the new environment where BS programs are more attractive, workers know there is a good substitute for working in traditional manufacturing occupations to accumulate occupation-specific human capital. Therefore, they reduce the chance of attachment to these occupations from the early phase of the life-cycle.

Finally, Figure 6 shows the average impact of the two reforms on life-cycle earnings across individuals. We find that both reforms lead to an increase in the average earnings, with a stronger effect in the case of the universal reform than of the targeted reform. This is not particularly surprising given the more generous feature of the universal reform. In both cases, the positive effect is the largest during the youth period, when many individuals take the apprenticeship. However, it is worth noting the positive impact diminishes as individuals age faster under the universal reform, and at around age 50, it becomes smaller than that of the targeted reform. This indicates that the targeted reform helps individuals to leave manufacturing occupations and transition into BS occupations, leading to higher growth of human capital towards the end of their working life.

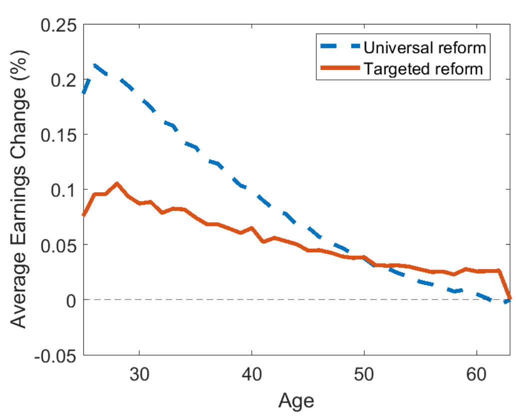
Figure 5: The Effect of BS-Targeted Exercise on Program and Occupation Choice Probabilities

(a) Education takeup (b) Occupation choice



Note: Figures show the effect of the targeted exercise, where a 10% wage subsidy is given to those who take up programs related to business-service (BS) occupations, on individuals' apprenticeship program and occupation choice probabilities. The left panel shows the effect on the choice probability of program take-up, while the right panel shows the impact on the occupation choice probabilities.

Figure 6: The Effect on Average Earnings along the Life cycle



Note: Figures show the effect of the universal exercise (blue dashed line) and the targeted exercise (red solid line) on average earnings across simulated individuals over the life cycle. In the universal exercise, a 10% wage subsidy is given to those who take up any programs, while in the targeted exercise, a 10% wage subsidy is given to those who take up programs related to business-service (BS) occupations.

7 Conclusion

In this paper, we have developed a theoretical framework to consider the joint decision of occupation choice and apprenticeship program taken by adult individuals. We first discussed the vocational nature of the Danish adult education system and introduced a new education classification to the literature on education program evaluation. Using the Danish administrative data and the local projection method, we have shown that the effect of business service education on working probability in the relevant occupation for workers in manufacturing and technology occupations is 0.9-3.1 percentage points in 1-8 years after participation. Mincer regression also shows positive effects on earnings in the relevant occupations for manufacturing and business-service occupations. Motivated by these findings, we develop a stylized model of occupation and program choice with flexible education program elasticities depending on occupations. We estimate the model by applying a technique in the dynamic discrete choice literature and find that the education switching elasticity is lower than the occupation choice elasticity, especially for those who are not employed. A policy counterfactual analysis suggests that the wage subsidy conditional on any education programs would expand the existing employment share inequality across occupation groups. In contrast, the subsidy targeted at the business-service-related programs would reduce the share of workers in the manufacturing sector significantly.

There are several benefits of considering the structural model of adult apprenticeship. First, our framework allows us to separate several mechanisms that affect occupation choices, such as non-monetary switching costs and occupation-specific human capital. Second, only by using the model can we formally describe different practical policy tools, such as wage subsidies specific to a group of programs, and evaluate the labor market and fiscal implications of hypothetical policy changes. We believe our proposal paves the way for further academic and policy discussion on the effective design of policies to promote education to adult individuals.

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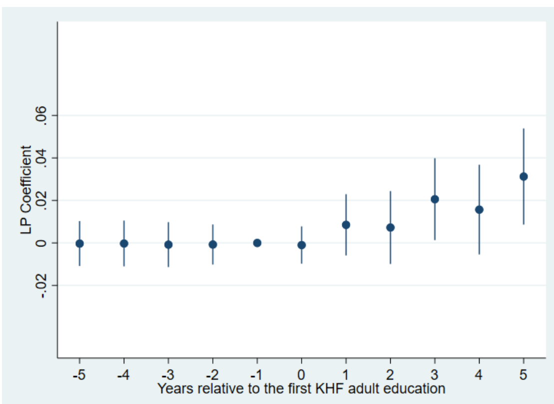
Appendix

A Additional Empirical Results

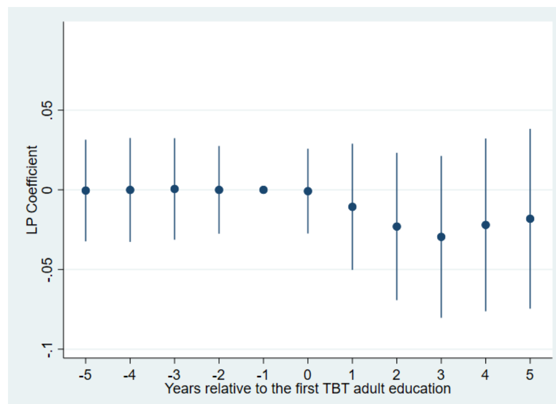
A.1 Dynamic DiD Analysis for Different Combinations of Past Occupation and Education Programs

Figure A.1: The Effect of Sectoral Education on Corresponding Sectoral Employment

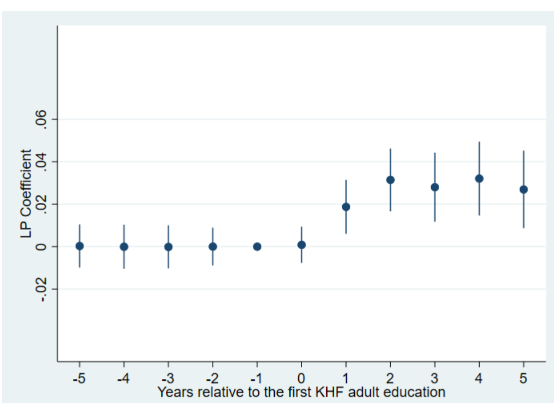
(a) From KHF employment to KHF education



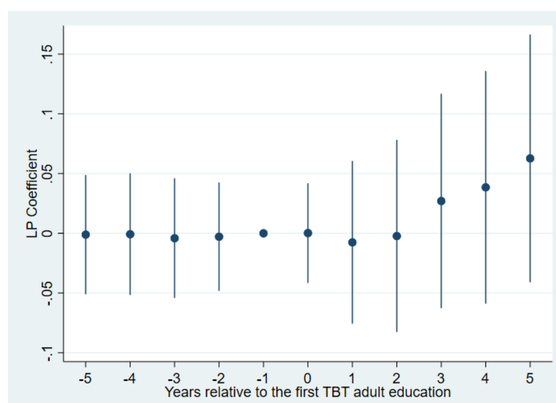
(b) From KHF employment to TBT education



(c) From TBT employment to KHF education



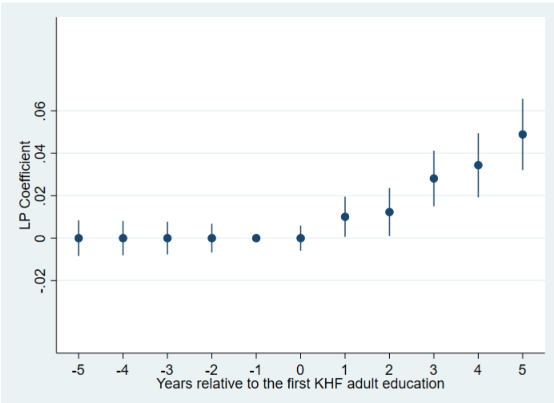
(d) From TBT employment to TBT education



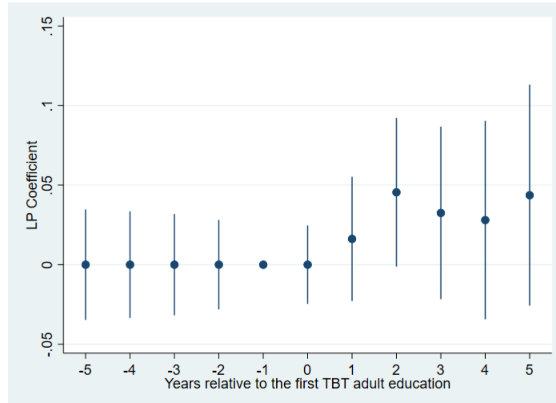
Note: The local projection estimates from equation (2) with the outcome variable of employment in each program category v are shown. Panel A.1a shows the case with the previous occupation of KHF and education category of KHF, so $(o, v) = (KHF, KHF)$, and panels A.1b, A.1c, and A.1d show the case with $(o, v) = (KHF, TBT), (TBT, KHF), (TBT, TBT)$, respectively. Error bars show the 95 percent confidence intervals. Standard errors are clustered at the individual and industry-year levels.

Figure A.2: The Effect of Sectoral Education on Overall Employment

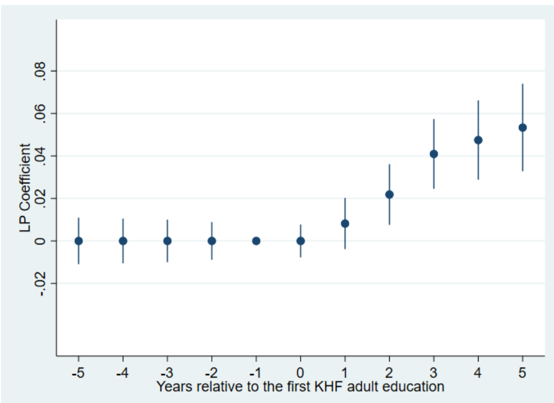
(a) From KHF employment to KHF education



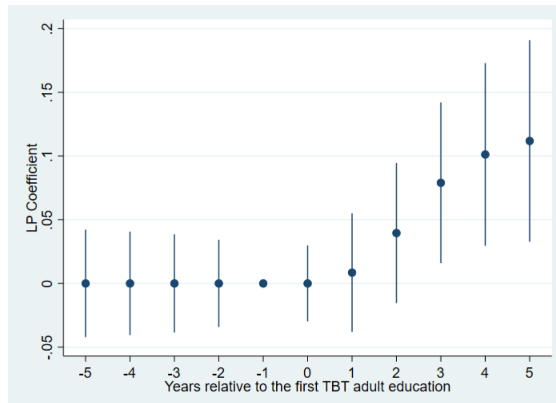
(b) From KHF employment to TBT education



(c) From TBT employment to KHF education



(d) From TBT employment to TBT education



Note: The local projection estimates from equation (2) with the outcome variable of overall employment. Panel A.1a shows the case with the previous employment sector of KHF and education sector of KHF, so $(s, v) = (KHF, KHF)$, and panels A.1b, A.1c, and A.1d show the case with $(s, v) = (KHF, TBT), (TBT, KHF), (TBT, TBT)$, respectively. Error bars show the 95 percent confidence intervals.

A.2 Cohort-Specific LP Estimates

Figure A.1 shows the estimation result of equation (1) with $(o, v) = (KHF, KHF)$. Figure A.2 shows the estimation result of equation (1) with $(o, v) = (KHF, TBT)$. Figure A.3 shows the estimation result of equation (1) with $(o, v) = (TBT, KHF)$. Figure A.4 shows the estimation result of equation (1) with $(o, v) = (TBT, TBT)$.

A.3 Robustness Checks for Mincer Regressions

Table A.1: Cohort-Specific Effects of KHF Education for KHF Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	k = -5	k = -4	k = -3	k = -2	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
KHF 1996	-0.000298	-0.00027	-0.000816	-0.000751	-0.000991	0.00853	0.00726	0.0206**	0.0157	0.0313***
	(0.0054)	(0.00551)	(0.00539)	(0.00481)	(0.00448)	(0.00735)	(0.00875)	(0.00983)	(0.0108)	(0.0115)
Observations	2278994	2278994	2278994	2278994	2278994	2278994	2278994	2278994	2278994	2278994
KHF 1997	0.00157	0.000312	-0.000456	-0.000144	-0.000982	-0.00797	-0.000113	0.00951	0.0174	0.0322**
	(0.0061)	(0.00577)	(0.00572)	(0.00516)	(0.0048)	(0.00825)	(0.0099)	(0.0112)	(0.0123)	(0.0131)
Observations	2452195	2452195	2452195	2452195	2452195	2452195	2452195	2452195	2452195	2452195
KHF 1998	-0.00585***	-0.00289**	-0.00128	-0.000952	-0.00102	0.00856***	0.0143***	0.0130***	0.0189***	0.0237***
	(0.00163)	(0.00147)	(0.00133)	(0.00121)	(0.00113)	(0.00199)	(0.00246)	(0.00281)	(0.0031)	(0.00334)
Observations	2865582	2865582	2865582	2865582	2865582	2865582	2865582	2865582	2865582	2865582
KHF 1999	-0.00646***	-0.00258	-0.00126	-0.000481	-0.00116	0.00459*	0.0103***	0.0129***	0.0184***	0.0222***
	(0.00223)	(0.00197)	(0.00172)	(0.00144)	(0.00133)	(0.0024)	(0.003)	(0.0035)	(0.00391)	(0.00423)
Observations	2919628	2919628	2919628	2919628	2919628	2919628	2919628	2919628	2919628	2919628
KHF 2000	-0.000257	0.0000422	-0.000719	-0.000281	-0.00155	-0.000428	0.0167***	0.0251***	0.0337***	0.0365***

	(0.00454)	(0.00398)	(0.00342)	(0.0028)	(0.00227)	(0.00423)	(0.00532)	(0.00627)	(0.00714)	(0.0078)
Observations	2995368	2995368	2995368	2995368	2995368	2995368	2995368	2995368	2995368	2995368
KHF 2001	-0.000893	-0.000492	-0.000818	-0.000798	-0.00217	0.0000943	0.00549	0.00592	0.0108	0.0235***
	(0.0052)	(0.00451)	(0.00383)	(0.00309)	(0.00245)	(0.00425)	(0.00531)	(0.00626)	(0.00717)	(0.00796)
Observations	3095244	3095244	3095244	3095244	3095244	3095244	3095244	3095244	3095244	3095244
KHF 2002	-0.000621	0.000249	0.000502	-0.000123	-0.0027	-0.00629	0.00378	-0.00733	-0.00389	-0.0174**
	(0.00596)	(0.0052)	(0.00435)	(0.00346)	(0.00274)	(0.00433)	(0.00535)	(0.0063)	(0.00725)	(0.00808)
Observations	3150114	3150114	3150114	3150114	3150114	3150114	3150114	3150114	3150114	3150114
KHF 2003	0.00367	0.000632	0.000747	0.000744	-0.00373	0.00263	-0.0104	0.0107	0.0198**	0.0132
	(0.00832)	(0.00731)	(0.00614)	(0.00477)	(0.00382)	(0.00556)	(0.00656)	(0.00771)	(0.00891)	(0.00998)
Observations	3227298	3227298	3227298	3227298	3227298	3227298	3227298	3227298	3227298	3227298
KHF 2004	0.0142	0.00912	0.00325	0.000298	0.00000753	0.0196***	-0.00997	0.0092	0.00488	0.0348***
	(0.0111)	(0.00978)	(0.00826)	(0.00637)	(0.00513)	(0.00693)	(0.00784)	(0.00896)	(0.0104)	(0.0117)
Observations	3230664	3230664	3230664	3230664	3230664	3230664	3230664	3230664	3230664	3230664

Note: The local projection estimates from equation (1) with the outcome variable of employment in the KHF sector are shown (so $v = KHF$ in equation 1). The sample is a group of workers that continuously worked in KHF sectors for five years prior to each treatment year (so $s = KHF$ in equation 1). Each row indicates the year of participation in KHF education (variable τ in equation 1). Within a row, each column indicates the lag and lead from the treatment year (variable k in equation 1). Standard errors are clustered at individual and industry-year levels and shown in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table A.2: Cohort-Specific Effects of TBT Education for KHF Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	k = -5	k = -4	k = -3	k = -2	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
TBT 1996	-0.000431	-0.0000661	0.000562	-0.0000182	-0.00082	-0.0106	-0.023	-0.0295	-0.022	-0.0182
	(0.0163)	(0.0166)	(0.0163)	(0.0141)	(0.0136)	(0.0202)	(0.0236)	(0.0259)	(0.0277)	(0.0288)
Observations	2605497	2605497	2605497	2605497	2605497	2605497	2605497	2605497	2605497	2605497
TBT 1997	-0.00166	-0.00177	-0.00169	-0.00147	-0.002	-0.0146	-0.0188	-0.0303	0.00819	0.00305
	(0.0306)	(0.0297)	(0.0294)	(0.0256)	(0.0247)	(0.0384)	(0.0453)	(0.05)	(0.0536)	(0.0559)
Observations	2797919	2797919	2797919	2797919	2797919	2797919	2797919	2797919	2797919	2797919
TBT 1998	-0.000568	-0.00113	-0.000612	-0.000544	-0.000696	-0.00452	-0.014	-0.0203	-0.0211	0.0121
	(0.0271)	(0.0245)	(0.0221)	(0.0195)	(0.0188)	(0.0298)	(0.0361)	(0.0403)	(0.0434)	(0.0455)
Observations	3057710	3057710	3057710	3057710	3057710	3057710	3057710	3057710	3057710	3057710
TBT 1999	-0.000973	-0.00104	0.00000342	0.000132	-0.000102	-0.0073	-0.0437*	-0.049	-0.0315	-0.0372
	(0.0218)	(0.0191)	(0.0165)	(0.0137)	(0.0131)	(0.0214)	(0.0261)	(0.0299)	(0.0326)	(0.0344)
Observations	3215949	3215949	3215949	3215949	3215949	3215949	3215949	3215949	3215949	3215949
TBT 2000	0.0000237	-0.000107	0.0000471	-0.000321	-0.000338	-0.0139	0.00903	0.0164	0.0442	0.0407

	(0.0206)	(0.0178)	(0.015)	(0.0121)	(0.0102)	(0.0173)	(0.0214)	(0.0248)	(0.0276)	(0.0294)
Observations	3368307	3368307	3368307	3368307	3368307	3368307	3368307	3368307	3368307	3368307
TBT 2001	-0.000227	-0.000252	-0.0000736	-0.000103	0.0000184	0.00543	0.00647	0.00941	0.0119*	0.0142*
	(0.006)	(0.00509)	(0.00419)	(0.00329)	(0.00269)	(0.00427)	(0.00527)	(0.00614)	(0.00689)	(0.00746)
Observations	3484336	3484336	3484336	3484336	3484336	3484336	3484336	3484336	3484336	3484336
TBT 2002	0.000254	0.000183	0.0000485	0.0000431	-0.0000635	0.0127***	0.00152	0.00349	0.00497	0.00432
	(0.00368)	(0.00314)	(0.00254)	(0.00194)	(0.00156)	(0.00225)	(0.00275)	(0.00322)	(0.00363)	(0.00396)
Observations	3562907	3562907	3562907	3562907	3562907	3562907	3562907	3562907	3562907	3562907
TBT 2003	-0.000828	-0.000515	-0.000159	-0.0000994	0.0001	0.00161	0.00214	0.00907**	0.00734	-0.000954
	(0.00554)	(0.00477)	(0.00389)	(0.0029)	(0.00235)	(0.00313)	(0.00362)	(0.00422)	(0.00476)	(0.00521)
Observations	3639885	3639885	3639885	3639885	3639885	3639885	3639885	3639885	3639885	3639885
TBT 2004	-0.0018	-0.000999	-0.000794	-0.000536	0.000164	-0.00602	-0.0193***	0.0144**	0.0188**	0.0116
	(0.0103)	(0.00895)	(0.00737)	(0.00548)	(0.00451)	(0.00565)	(0.00622)	(0.00697)	(0.00785)	(0.00859)
Observations	3637130	3637130	3637130	3637130	3637130	3637130	3637130	3637130	3637130	3637130

Note: The local projection estimates from equation (1) with the outcome variable of employment in the TBT sector are shown (so $v = TBT$ in equation 1). The sample is a group of workers that continuously worked in KHF sectors for five years prior to each treatment year (so

$s = KHF$ in equation 1). Each row indicates the year of participation in TBT education (variable τ in equation 1). Within a row, each column indicates the lag and lead from the treatment year (variable k in equation 1). Standard errors are clustered at individual and industry-year levels and shown in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table A.3: Cohort-Specific Effects of KHF Education for TBT Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	k = -5	k = -4	k = -3	k = -2	k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
KHF 1996	0.0003	-0.0000447	-0.000121	0.0000263	0.000849	0.0188***	0.0315***	0.0280***	0.0321***	0.0270***
	(0.00519)	(0.0053)	(0.00518)	(0.00453)	(0.00437)	(0.00649)	(0.00755)	(0.00831)	(0.00888)	(0.00932)
Observations	2387733	2387733	2387733	2387733	2387733	2387733	2387733	2387733	2387733	2387733
KHF 1997	0.00000296	-0.000236	-0.000319	-0.000252	0.000455	0.0234***	0.0264***	0.0242***	0.0305***	0.0330***
	(0.00534)	(0.00517)	(0.00511)	(0.00451)	(0.00434)	(0.00674)	(0.00794)	(0.0088)	(0.00944)	(0.00993)
Observations	2549177	2549177	2549177	2549177	2549177	2549177	2549177	2549177	2549177	2549177
KHF 1998	0.00063	0.000186	-0.0000555	-0.0000454	0.0000903	0.0037	0.00787***	0.0118***	0.0161***	0.0186***
	(0.00207)	(0.00191)	(0.00178)	(0.00159)	(0.00153)	(0.00243)	(0.00294)	(0.0033)	(0.00357)	(0.00377)
Observations	2725979	2725979	2725979	2725979	2725979	2725979	2725979	2725979	2725979	2725979
KHF 1999	0.00121	0.000781	0.000407	0.000122	0.000359	0.00704**	0.0124***	0.0168***	0.0162***	0.0168***
	(0.00269)	(0.0024)	(0.00215)	(0.0018)	(0.00173)	(0.00282)	(0.00344)	(0.00395)	(0.00433)	(0.0046)
Observations	2897288	2897288	2897288	2897288	2897288	2897288	2897288	2897288	2897288	2897288
KHF 2000	0.000811	0.000582	0.000337	0.000102	0.000142	0.0145***	0.00943*	0.0199***	0.0257***	0.0218***

	(0.00457)	(0.004)	(0.00346)	(0.00281)	(0.00239)	(0.00406)	(0.00503)	(0.00583)	(0.00655)	(0.00706)
Observations	2973817	2973817	2973817	2973817	2973817	2973817	2973817	2973817	2973817	2973817
KHF 2001	0.00034	0.000309	0.0000978	0.0000302	-0.00012	0.0155***	0.0258***	0.0263***	0.0422***	0.0475***
	(0.00441)	(0.00379)	(0.00322)	(0.00256)	(0.00207)	(0.00338)	(0.00419)	(0.00489)	(0.00553)	(0.00607)
Observations	3049943	3049943	3049943	3049943	3049943	3049943	3049943	3049943	3049943	3049943
KHF 2002	0.000881	0.000709	0.000416	0.000165	-0.000198	0.00769**	0.00207	0.0177***	0.00566	0.00509
	(0.005)	(0.00432)	(0.00359)	(0.00278)	(0.0022)	(0.00333)	(0.00409)	(0.00481)	(0.00547)	(0.00604)
Observations	3043479	3043479	3043479	3043479	3043479	3043479	3043479	3043479	3043479	3043479
KHF 2003	0.000971	0.000985	0.000708	0.000436	-0.00024	0.00295	0.00449	0.0149***	0.0182***	0.0265***
	(0.00607)	(0.00528)	(0.0044)	(0.00332)	(0.00262)	(0.00366)	(0.00431)	(0.00506)	(0.00579)	(0.00643)
Observations	3070553	3070553	3070553	3070553	3070553	3070553	3070553	3070553	3070553	3070553
KHF 2004	-0.000278	-0.000084	0.00000901	0.0000815	0.0000096	0.0363***	0.0257***	0.0657***	0.0455***	0.0341***
	(0.0127)	(0.0111)	(0.00934)	(0.00701)	(0.00559)	(0.0073)	(0.00822)	(0.00937)	(0.0107)	(0.012)
Observations	3004898	3004898	3004898	3004898	3004898	3004898	3004898	3004898	3004898	3004898

Note: The local projection estimates from equation (1) with the outcome variable of employment in the KHF sector are shown (so $v = KHF$ in equation 1). The sample is a group of workers that continuously worked in TBT sectors for five years prior to each treatment year (so $s = TBT$

in equation 1). Each row indicates the year of participation in KHF education (variable τ in equation 1). Within a row, each column indicates the lag and lead from the treatment year (variable k in equation 1). Standard errors are clustered at individual and industry-year levels and shown in parentheses. *** $p<0.01$ ** $p<0.05$ * $p<0.1$.

Table A.4: Cohort-Specific Effects of TBT Education for TBT Workers

	(1) k = -5	(2) k = -4	(3) k = -3	(4) k = -2	(5) k = 0	(6) k = 1	(7) k = 2	(8) k = 3	(9) k = 4	(10) k = 5
TBT 1996	-0.00112	-0.00076	-0.00411	-0.00286	0.000171	-0.00758	-0.0023	0.027	0.0385	0.0627
	(0.0255)	(0.026)	(0.0256)	(0.0232)	(0.0213)	(0.0348)	(0.041)	(0.0458)	(0.0497)	(0.0529)
Observations	2488492	2488492	2488492	2488492	2488492	2488492	2488492	2488492	2488492	2488492
TBT 1997	-0.000054	0.00131	0.00203	0.00367	0.00349	0.00733	0.0115	0.0362*	0.0336	0.017
	(0.0119)	(0.0113)	(0.0113)	(0.0103)	(0.00948)	(0.0163)	(0.0194)	(0.0218)	(0.0237)	(0.0253)
Observations	2657575	2657575	2657575	2657575	2657575	2657575	2657575	2657575	2657575	2657575
TBT 1998	0.0077	0.00681	0.00305	0.00309	-0.001	0.104***	0.132***	0.124***	0.133***	0.130***
	(0.0149)	(0.0137)	(0.0126)	(0.0117)	(0.0107)	(0.0188)	(0.0231)	(0.0261)	(0.0286)	(0.0306)
Observations	2792649	2792649	2792649	2792649	2792649	2792649	2792649	2792649	2792649	2792649
TBT 1999	-0.000641	0.00138	-0.00275	-0.000156	0.00187	-0.00547	-0.0587**	-0.0354	-0.0454	-0.0482
	(0.0207)	(0.0187)	(0.0167)	(0.0141)	(0.0128)	(0.023)	(0.0285)	(0.033)	(0.0366)	(0.0394)
Observations	2985183	2985183	2985183	2985183	2985183	2985183	2985183	2985183	2985183	2985183
TBT 2000	-0.0116	-0.00693	-0.00522	-0.00631	0.00261	-0.00264	0.0265	0.0842***	0.0879***	0.0727**

	(0.021)	(0.0187)	(0.0165)	(0.0135)	(0.0109)	(0.0203)	(0.0254)	(0.0298)	(0.0339)	(0.037)
Observations	3083720	3083720	3083720	3083720	3083720	3083720	3083720	3083720	3083720	3083720
TBT 2001	-0.0012	-0.000154	0.00113	0.00109	0.000811	-0.0152**	-0.000093	0.00798	0.0102	0.0235*
	(0.00812)	(0.00715)	(0.00621)	(0.00508)	(0.00397)	(0.00699)	(0.0087)	(0.0102)	(0.0117)	(0.013)
Observations	3163236	3163236	3163236	3163236	3163236	3163236	3163236	3163236	3163236	3163236
TBT 2002	-0.000851	-0.000241	0.000945	0.001	0.000208	0.0128***	0.0247***	0.0306***	0.0484***	0.0423***
	(0.00441)	(0.00389)	(0.00332)	(0.00268)	(0.00209)	(0.00339)	(0.00418)	(0.00491)	(0.00564)	(0.0063)
Observations	3183146	3183146	3183146	3183146	3183146	3183146	3183146	3183146	3183146	3183146
TBT 2003	0.00491	0.00416	0.00269	0.00114	-0.00217	0.00677*	0.00315	0.0152***	0.0148**	0.000662
	(0.00523)	(0.00464)	(0.00395)	(0.00309)	(0.00244)	(0.00367)	(0.00436)	(0.00513)	(0.00593)	(0.00667)
Observations	3207302	3207302	3207302	3207302	3207302	3207302	3207302	3207302	3207302	3207302
TBT 2004	-0.000884	-0.00269	-0.00579	-0.00468	0.00456	-0.0279**	0.00543	0.0486***	0.0406**	0.0692***
	(0.0206)	(0.0184)	(0.0157)	(0.0122)	(0.00965)	(0.0134)	(0.0154)	(0.0177)	(0.0206)	(0.0235)
Observations	3120133	3120133	3120133	3120133	3120133	3120133	3120133	3120133	3120133	3120133

Note: The local projection estimates from equation (1) with the outcome variable of employment in the TBT sector are shown (so $v = TBT$ in equation 1). The sample is a group of workers that continuously worked in TBT sectors for five years prior to each treatment year (so $s = TBT$

in equation 1). Each row indicates the year of participation in TBT education (variable τ in equation 1). Within a row, each column indicates the lag and lead from the treatment year (variable k in equation 1). Standard errors are clustered at individual and industry-year levels and shown in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table A.5: Mincer Equation with Time Fixed Effects

	log earnings			
	AgFood.	Manuf.	BusSer.	PerSer.
Tenure	0.0199***	0.0130***	0.0141***	0.0125***
	(0.0010)	(0.0001)	(0.0002)	(0.0004)
Training	-0.0766	0.0265***	0.0211***	-0.0476*
	(0.0649)	(0.0073)	(0.0028)	(0.0195)
Age controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N	148611	6152134	4133980	6591667

Note: Estimation results of the modified Mincer equation (3) with the time fixed effect are shown. "AgFood" stands for the Agriculture and Food (FJO) occupations, "ManTec" for Manufacturing and Technology (TBT) occupations, "BusSer" for Business service (KHF) occupations, and "PerSer" for Personal Service (OSP) occupations. Standard errors are clustered at the individual and industry-year levels.

Table A.6: Mincer Equation with the Lagged Outcome Variable

	log earnings			
	AgFood.	Manuf.	BusSer.	PerSer.
Tenure	0.00905***	0.00336***	0.00576***	0.00237***
	(0.000568)	(0.0000988)	(0.0000906)	(0.000129)
Training	-0.0881	0.0156**	0.00623**	-0.0556***
	(0.0638)	(0.00704)	(0.00265)	(0.0188)
L.log earnings	0.0346***	0.0984***	0.129***	0.145***
	(0.00313)	(0.000829)	(0.000892)	(0.00106)
Age controls	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
N	148611	6152134	4133980	6591667

Note: Estimation results of the modified Mincer equation (3) with the lagged log earnings are shown. "AgFood" stands for the Agriculture and Food (FJO) occupations, "ManTec" for Manufacturing and Technology (TBT) occupations, "BusSer" for Business service (KHF) occupations, and "PerSer" for Personal Service (OSP) occupations. Standard errors are clustered at the individual and industry-year levels.