Skill Overshooting in Job Training with the Trade Adjustment Assistance Program

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Abstract

We investigate the training choices made by workers entering the Trade Adjustment Assistance (TAA) program and their post-exit outcomes. This is important as more workers enter these types of programs due to technological change and globalization. We show that workers that choose a training occupation beyond their skill level (skill overshooting) achieve higher earnings ($615 annually) and wage replacement rates (2.0 percentage points) at the cost of lower reemployment rates (-1.9 percentage points) immediately following program exit. An investigation of subsamples shows that skill overshooting is especially beneficial to females and those living in rural areas with earnings gains of $1,443 and $1,080, respectively, without hurting their chances of reemployment.

Keywords: TAA, job training, wage replacement, ALMP
JEL: J08, J68, F16

I. Introduction

Recent labor market experiences during the Great Recession and thereafter have brought worker dislocation and reemployment into the center stage of policy discussions. However, worker dislocation is an ongoing, centuries-old societal issue. As technology advances, the skills in demand at any point in time constantly changes, and this adds to the adjustment costs of dislocation as acquiring new skills is sometimes necessary for reemployment. Rapid globalization further accelerates changes in skill demands across industries. In an effort to lower the adjustment costs of dislocated workers in this environment, governments around the world offer various active labor market programs (ALMPs) to dislocated workers to help with reemployment (Barnow & Smith, 2016).[1]

This paper evaluates one such program by focusing on the job training provision of the Trade Adjustment Assistance (TAA) program. We investigate whether the training, when participants take it as a chance to upgrade their skills, can provide an extra boost to their post-participation earnings. The TAA program is a dislocated worker program administered by the U.S. Department of Labor that is designed to help those whose employment is adversely affected by foreign competition.[2] We use the TAA participants' data because of the information that it provides on the services each participant received as well as detailed

[1] Barnow and Smith (2016) give a comprehensive description of the U.S. ALMPs and a survey of the program evaluation literature on those programs. Card, Kluve, and Weber (2010, 2018) provide two meta studies of ALMPs globally.

[2] Many countries offer some form of an adjustment assistance program for those negatively affected by globalization. The Austrian Steel Foundation and Mexico's PROBECAT closely resemble the U.S. TAA program in services provided including job training. Many other programs offer income assistance or payroll protection to prevent displacement (European Union's Compensation Payments in EU agriculture under Common Agricultural Policy, Mexico's PROCAMPO, and Argentina's REPRO). See Lederman, Lopez-Acevedo, and Savchenko (2014) for more detail.

information on the individual participants. There is a particular emphasis on job training in the TAA based on the idea that import competing tasks are being replaced by foreign competition at an increasing rate (Acemoglu, Autor, Dorn, Hanson, & Price, 2016; Autor, Dorn, & Hanson, 2016), rendering the skill sets possessed by the TAA eligible workers practically obsolete in the United States. Marcal (2001) shows that TAA participants are older, have a longer tenure at their previous employment, and have a much lower chance of being recalled by their previous employer compared to Unemployment Insurance (UI) recipients in the manufacturing sector. To secure a sustainable career path, obtaining new sets of skills still marketable in the U.S. is deemed necessary.

Many studies have investigated the impacts of participating in the TAA and receiving job training on labor market outcomes and the findings are inconclusive. Using a survey data of TAA participants around 1988 when the emphasis of the program shifted toward training provisions, Decker and Corson (1995) show that TAA participants suffer a greater wage loss (wage replacement rate of 0.76) compared to displaced manufacturing workers in general and they do not find any significant impact of TAA training on post-participation earnings. Marcal (2001) confirms their findings on the impact of TAA training on earnings but finds that it has positive impacts on employment. In more recent studies, Reynolds and Palatucci (2012) use the same TAA participant data used in our study and find similar patterns as those in Marcal (2001). Schochet, D'Amico, Berk, Dolfin, and Wozny (2012), in their large survey study, show that TAA participants suffer negative impacts on both employment and earnings compared to non-TAA displaced workers, but TAA training reduces such negative impacts compared to non-trainees. From a different perspective, Barnette and Park (2017) find that TAA training enrollment is beneficial in reducing the negative impacts of a large increase in local unemployment.

Our paper goes one step further into examining participants' choices of training occupations and how those choices can be used as a chance to improve their skill levels.[3] Specifically, we examine a choice of a training occupation that is beyond their skill level compared to a choice of an occupation that is at their skill level or below. We use their educational attainment as a proxy for skill level to define *skill overshooting* as a participant choosing to train for an occupation where the average job holder of that occupation has at least one more year[4] of education compared to the participant.[5] We construct the comparison group – TAA trainees that did not overshoot – using nearest neighbor matching with replacement on a propensity score to minimize the selection bias that is inherent in any voluntary program participation. Andersson, Holzer, Lane, Rosenblum, and Smith (2013) document that the selection into training enrollment within a program is less of an issue compared to the selection into participating in the program itself. We expect that the selection issue in our analysis is even smaller as we compare skill overshooters to non-overshooters among TAA trainees.

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[3] Park (2012) is another study that looks closely at the job training provision of the TAA program. They show that only 32% of the TAA trainees find a job in the occupation for which they receive training and those who found a job in their training occupation enjoy a small yet statistically significant advantage in post-exit earnings. However, the majority of TAA trainees manage to find a job even if the new job is not in their training occupation; they might be able to use the training opportunity to improve their post-participation job prospects.

[4] We also run the estimations using a two-years-or-more threshold as an alternative definition of skill overshooting. The results are very similar.

[5] We discuss our use of education as the proxy for skill level in more detail in section IV.

Carefully selecting a comparison group through propensity score matching reduces the selection issue further.

We find that skill overshooting improves trainees' earnings potential, but it hurts their chance of finding a job. Specifically, it increases their wage replacement rates by 2.0 percentage points (pps) and $615 in annual earnings compared to trainees who did not overshoot during the three quarters immediately following the program exit. But the chance of reemployment falls by 1.9 pps.

We also investigate the impacts of skill overshooting for subsamples based on gender, age, urban/rural-ness of their local labor market, and schooling beyond/below high school level. We find that skill overshooting affects different groups of trainees differently. We find the most drastic differences in gender subsamples. Overshooting is highly beneficial for female trainees who see a much larger increase in earnings (4.1 pps in wage replacement rate and $1,443 in annual earnings) and no discernable impact on the chance of reemployment. In contrast, male trainees suffer from a decline in their reemployment rate (-3.1 pps) without much benefit to their earnings ($173). Trainees in rural areas also benefit more from skill overshooting with an earnings increase of $1,080 without the negative reemployment effect. The findings on these subsamples suggest that overshooting is especially effective in improving the labor market outcomes of particularly disadvantaged groups of workers based on pre-participation characteristics. Trainees with more than a high school education also enjoy a large gain in earnings ($1,186), but not without the cost of lower reemployment rate (-1.7 pps). We find very small and statistically insignificant differences between older (age 43-65) and younger (age 18-42) workers.

The main contribution of this study is that we look deeply at the choices workers make toward their next career after a layoff, especially the trade-displaced workers to whom acquisition of new skills is deemed necessary for reemployment. Liu and Trefler (2019) is the closest to our study in the sense that they focus on the behavioral aspect of occupation switching among the workers whose displacement is connected to rising import competition. They examine the impact of trade in services with China and India on U.S. labor market outcomes by studying how this impacted unemployment and earnings for the period of 1996-2007. They distinguish workers who switch to an occupation that pays more on average than their current occupation (upward switching) and those who switch to an occupation that pays less on average than the current occupation (downward switching). They find that rising service imports from China and India over the past decade have increased the incidence of downward switching by 17%, while upward switching has only increased by 4% over the past decade. They find that workers leaving import-competing occupations face higher chances of downward switching. Kosteas and Park (2015) is another study that explores the occupation switching behavior of trade-displaced workers. They trace workers transitioning away from import-competing occupations and find that the cross-occupation movement of trade-displaced workers has a significant negative impact on the wages of the incumbent workers in the receiving occupations as well as the trade-displaced workers entering these occupations.

With the help of rich information on TAA services rendered to each participant, this study goes one step further than simply observing occupations before and after a layoff. We look at the job training choices, which lie between the two employments observed in other datasets, as workers’ intentions or strategies for their future employment prospects.

This paper also complements previous research on the positive transitions from industrial switching behavior of the trade-displaced. Autor, Dorn, Hanson, and Song (2014) show a positive impact of industry-switching among the trade-displaced workers in response to rising exposure to Chinese imports between 1990 and 2007. They find a large and negative impact on the cumulative earnings in general but show that the workers who switch industries, though still within the manufacturing sector, experience a positive impact on their earnings. Hyman (2018) also finds positive impacts of industry-switching on earnings.[6]

Our study has policy relevance. The large emphasis of the TAA program on training provisions and the mixed results on impacts of training in empirical studies discussed above suggest that enrolling in training alone does not guarantee well-paying jobs for the participants. Many studies show that the quality of the match between a worker and a job is important for the determination of wages and the retention rate (Andrews, Gill, Schank, & Upward, 2012; Shimer & Smith, 2000; Abowd, Kramarz, & Margolis, 1999). A good match between a TAA trainee and a training program could lead to similar effects. Mack (2009) finds that the training occupation choice is made with substantial interactions with TAA staff through worker assessment and career counseling. This implies that the program administration has influence over the process that can lead to improvements in the program outcomes.

The rest of the paper is organized as follows. Section II describes the TAA program in more detail. Section III presents the data sources, section IV shows the variable definitions and

[6] Hyman (2018)'s sample covers the workers eligible for TAA benefits (employed at an establishment in Longitudinal Employer-Household Dynamics (LEHD) data matched to a certified TAA petition) rather than those who participated in TAA.

summary statistics on skill overshooting, section V discusses our methodology, section VI presents the findings and section VII concludes.

II. Trade Adjustment Assistance and Job Training Provisions

The Trade Adjustment Assistance (TAA) is a dislocated worker program administered by the U.S. Department of Labor (DOL) that is designed to help those whose employment is adversely affected by foreign competition. TAA provides a variety of services to eligible workers such as job search assistance, financial support for physical relocation, job training, remedial education, extended unemployment insurance benefits, and Health Insurance Tax Credits (HITC).[7] These services are provided at American Job Centers (AJCs) located throughout the country. AJCs serve all federal employment and training services that are administered under the umbrella of the Workforce Innovation and Opportunity Act (WIOA)[8] which includes TAA.

When three or more workers at an establishment are laid off due to import competition, they (or a representative – union, AJC staff, or the company itself) can file a petition with the DOL. Petitions are filed at the establishment-level representing one physical location.[9] Once the petition is certified, workers whose employment is reduced or terminated between the first

[7] For more details on the petition process and the complete list of services, see Park (2012).

[8] WIOA replaced the Workforce Investment Act of 1998 (WIA) in July 2015.

[9] If multiple locations of one firm are experiencing trade-related layoffs at the same time, each location can file a separate petition, or a representative can file one petition for multiple locations. In the case where one petition covers multiple locations, separate petition forms must be filled out for each location with information on the physical location for investigative purposes. A separate petition number (same numeric petition number + an alphabetical suffix) is assigned to each location in that case.

day layoffs began and two years from the date of petition certification, are eligible for TAA benefits.

TAA emphasizes job training provisions as trade-displaced workers tend to possess skill sets that are increasingly less marketable in the U.S. To determine participants' training needs, TAA offers worker assessment, counselling, and career planning services with staff members at AJCs. Job training can be delivered by various modes: classroom training, on-the-job training (OJT), and customized training. Classroom training is offered through job training programs at vocational schools and community colleges. OJT is provided directly by an employer where a trainee is essentially an employee of the company providing the training. In this case, the TAA subsidizes 50% of their wages for up to six months. Customized training is similar to OJT in that the skill sets taught through these programs are designed to meet specific needs of a certain employer, but post-training employment is not guaranteed. This training can last up to two years. TAA participants are also eligible to receive remedial training for up to six months in addition to job training. Remedial training covers English as a Second Language, GED preparation, and basic math classes. TAA trainees receive income support for the duration of training as extended UI benefits for up to two years. Remedial trainees can receive an additional 26 weeks of UI benefits.

III. Data

a. Trade Act Participant Report (TAPR) and TAA Petition Data

The DOL manages two separate datasets regarding the Trade Adjustment Assistance program: one for the petitions and the other for the participants. The Trade Act Participant Report (TAPR) collects information on TAA participants. This dataset consists of three sections: (1) participant characteristics, (2) services and benefits delivered during participation, and (3) labor market outcomes after exit. The data was acquired through a Freedom of Information Act request. Our sample covers 320,603 workers who participated in the TAA program from 1998 to 2007.

The first section of the data covers information on the individual characteristics of participants such as gender, age, race/ethnicity, education, English language proficiency, and tenure with the previous employer. It also reports the date of participation, the TAA petition number that the participant is certified under, and earnings during the three quarters prior to participation.[10] The second part of the data on services and benefits contains information on training provisions such as the modes of training (classroom, customized, on-the-job, or remedial), occupation of training, and the duration of training. It also shows various forms of financial support participants received during participation. The outcome portion of the TAPR covers employment status and earnings during the three quarters following the program exit. Occupation of reemployment and the date of program exit are also reported here.

In this study, we make heavy use of training and reemployment occupations. Both are reported using the Standard Occupational Classification (SOC) system and we use the 6-digit version in this study. Among participants who received any job training, 56.70% of them have a valid 6-digit SOC. The reporting rate for the reemployment occupation is even lower at 26.71%.[11] The issue of occupation code reporting quality should not bias the estimation results

[10] These three quarters are calendar quarters leading up to participation rather than the last three quarters of previous employment. As a result, some of reported earnings are not from the TAA qualifying employment and are invalid for the purpose of this study. We detail the issues and construction of earnings variables in Appendix A1 which is available on the author's website.

[11] For more details on occupation reporting quality, see Appendix A2 which is available on the author's website.

unless the poor reporting is systematically biased in one direction. States are subject to performance evaluations based on (1) reemployment rates, (2) retention rates, and (3) post-exit earnings. Occupations of training and reemployment do not enter into performance evaluation. Therefore, we have no reason to believe that there is a systemic bias in the quality of occupation code reporting.

We utilize information on the participant's geographic location to control for the labor market characteristics of their local areas. We link the TAA petition data to TAPR using the petition numbers and use the zip code of the previous employer as a proxy for the participant's location. We then use the zip code and the city/state pair to identify the commuting zone of each participant.

Panel A of Table 1 shows the summary statistics for TAA participant characteristics. They are on average, 43.88 years old, received 12.26 years of schooling, and made about \$34,957 annually in 2000 US dollar (USD) values.[12] We also compare the characteristics of selected subgroups – gender, age (43-65 vs. 18-42), geography (urban vs. rural), and education (11 years or less vs. 13 years or more). The starkest difference we notice between subgroups is the differences in their pre-participation earnings. Not surprisingly, the difference is the largest for the education subgroup where the high-education sample made 65% more than the low-education counterparts on average. The gender subsamples show a similar disparity; male participants earned 51% more than female participants. We also see that location matters a lot. Participants living in an urban area make 29% more than their rural counterparts.

[12] Our sample aligns well with the statistics of TAA eligible workers between 2008 and 2009 from Dolfin and Berk (2010) where they document that TAA eligible workers are older, less educated, and received higher earnings prior to displacement, compared to both unemployed workers in general and unemployed manufacturing workers.

[Table 1 about here]

Panel B shows the enrollment statistics for various modes of training programs.[13] 65.43% of all participants received a form of job training (classroom, customized, or on-the-job training). The vast majority (97.72%) of job training takes the form of classroom training. Age is a definitive factor in deciding whether to receive job training. 76.54% of younger participants received training compared to 63.09% of older participants. The low-education sample (less than high school) has a relatively high rate of remedial training enrollment (35.60%) as it offers GED and ESL classes. Despite the fact that participants are eligible for job training in addition to remedial training, only 46.18% of the low-education sample receives job training, a remarkably low rate compared to the other subsamples. The training enrollment pattern is quite distinctive between male and female participants as well. Female participants show a higher rate of both job training and remedial training than male participants.

Panel C summarizes the labor market outcomes of the participants. 77.20% of them found employment within the three quarters of exiting the program. At the new job, they make annual earnings of $26,798 on average which is around 86.53% of their previous earnings. Participants who received job training show a slightly higher rate of reemployment, but slightly lower earnings compared to all participants. This pattern holds for most subsamples.

Without accounting for selection into job training, we are cautious with comparing the outcomes of all participants and job trainees. One pattern that arises from all subsamples is that job training seems to narrow the gap between advantaged and disadvantaged groups in both reemployment rates and earnings. The largest gap, again not surprisingly, occurs in the education subsample in terms of both reemployment rates and earnings, but training narrows

[13] See Park (2012) for more detailed statistics and analysis of the efficacy of different training modes.

the gap in the reemployment rate substantially. The disadvantage that female and rural participants display in pre-participation earnings remains after exiting the program. However, the magnitude of the disadvantage decreases with participation, and the magnitude decreases further with job training.

b. Current Population Survey (CPS)

Public-use Current Population Survey (IPUMS CPS) data together with TAPR data is used to construct our main variable, skill overshooting. We construct skill overshooting by comparing a participant's skill level to the skill level of the training occupation. We use educational attainment as a proxy for skill level. The participant's years of schooling are taken directly from TAPR. Occupation-level educational attainment is constructed using IPUM-CPS as the average years of schooling for job holders of each occupation each year. CPS reports occupations using 3-digit Census Occupation Codes (COCs). We crosswalk this to 6-digit SOC codes to be merged with TAPR for the year of participation.[14]

c. Local Labor Market Characteristics

We incorporate two aspects of participants' local labor markets: unemployment rate at the time of program exit and an urban-rural designation. Following recent literature such as Autor, Dorn, and Hanson (2013), we use commuting zones (CZs) as our unit of geographic disaggregation since they represent separate labor markets identified by commuting patterns.

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[14] There is a unique matching between SOCs and COCs in that 752 SOCs uniquely map into 482 COCs. We use SOCs rather than COCs for the analysis to preserve more variation in our sample. COCs are narrowly defined; therefore, the choosing of SOC as our occupation identification rather than COC is expected to be marginal.

We use the 2003 version of the Urban-Rural Continuum Code published by the U.S. Department of Agriculture to construct the urban-rural designation of CZs. In this dataset, each county is identified on a 9-point scale with 1 being the most urban and 9 being the most rural based on whether a county is in a metro area, whether a county is adjacent to a metro area, and the size of urban population in the county. We aggregate this county-level designation to the CZ-level to identify a CZ as urban, rural, or in-between. A CZ is classified as urban if all counties in the CZ are in a metro area or adjacent to a metro area. A CZ is classified as rural if no county in the CZ is a metro area. Out of 708 CZs in the U.S., 298 of them are identified as urban and 297 as rural.

For the unemployment rates, we use Local Area Unemployment Statistics (LAUS). LAUS provides labor market statistics at various levels of geographic disaggregation from state-level to city-level. This data is managed by BLS and is constructed from merging various sources of labor market data. We use county-level statistics aggregated to the CZ-level.

IV. Definitions and Summary Statistics

Our main variable, *skill overshooting*, captures a trainee's intention to improve her skill level by choosing a training occupation that is of higher skill level than her own. In this study, we use educational attainment measured in years of schooling as a proxy for skill levels. Accordingly, skill overshooting ($Skill\_OS_i$) is defined as the following:

$$Skill\_OS_i = \text{Average schooling of trainee } i\text{'s training occupation} - i\text{'s schooling} \qquad (1)$$

The information on participants' schooling is obtained from TAPR. The average schooling of a trainee's training occupation is measured as the average years of schooling for job holders of the occupation in the CPS.[15]

Using skill overshooting defined above, we also construct an indicator variable for overshooting, I_OS_i. We consider a two-year (±1 year) band around the participant's own education to represent her skill-level. If a participant chooses a training occupation with the average schooling above the band, we say she is overshooting and assign the value of one to I_OS_i.

$$I\_OS_i = 1 \qquad \text{if } Skill\_OS_i > 1; \quad 0 \text{ otherwise} \tag{2}$$

Admittedly, educational attainment alone does not capture the full extent of the skill level of a person; however, we believe it is the most suitable measure of one's skill level for our analysis of TAA participants for it is a good measure of one's general skills that are transferrable across employment. The literature discusses an individual worker's skill level to be comprised of general skills and specific skills. General skills are specific to an individual worker and are accumulated through education and overall labor market experiences. Specific skills are tied to one's employment. There are firm-specific factors such as firm-level productivity and efficiency wages and factors specific to firm-worker matching such as within-firm seniority (Kletzer, 1989; Topel, 1991). These firm-specific factors are not transferrable across employers. More recent studies focus on task-specific skills that could be transferrable across employers if a worker finds a job in a similar occupation (Gibbons, Katz, Lemieux, &

[15] We use IPUMS CPS data to construct occupational education levels rather than TAPR because CPS is more representative of the general workforce while TAA participants tend to be skewed toward less-educated, low-skilled workers.

Parent, 2005; Kambourov & Manovskii, 2009, Gathmann & Schönberg, 2010). TAA participants are likely to lose both firm-specific and task-specific skills as the majority of them move away from their previous employers, occupations, and industries. Our data shows that only 1.81% of TAA participants report expecting to be recalled by the previous employer. According to Marcal (2001), 86.9% of TAA trainees switch industries (2-digit SIC) and 80.2% switch occupations (2-digit SOC[16]).[17]

While several of the studies cited in this paper use wage rates to convey information on various aspects of one's skill sets, wage rates are not the proper measure of the level of one's general skills that is relevant for our study. A large portion of wage rates is based on specific skills. Davidson, Heyman, Matusz, Sjöholm, and Zhu (2014) show that a substantial portion of one's wage rate is specific to worker-firm matching in their analysis of the impacts of rising import competition on the quality of assortative matching. Gathmann and Schönberg (2010) also find that the wage rate is largely associated with task-specific skills.[18] In this study, we compare a participant's skill level to the level of general skills associated with a certain occupation. Although the level of general skills depends on both education and overall labor market experiences of a participant, we use years of schooling as a proxy for general skills and

[16] SOC codes are of 8 digits with the first two digits defining job families, the next four digits detailing occupations, and the last two digits offering subcategories of an occupation. Occupations in which the first two digits are different do not share many common tasks.

[17] TAPR reports 4-digit SIC codes of the previous employer but not of the post-exit employer, and occupations of post-exit employment but not of the previous employment. For this reason, we cannot measure the rate of industry and occupation switching for our sample.

[18] Gathmann and Schönberg (2010) construct skill distances between occupations and find that a job switch with a long skill distance leads to larger wage losses of about 10 percentage points.

leave out the general labor market experiences as it is difficult to construct a meaningful measure of overall labor market experience required for an occupation.

Panel A of Table 2 summarizes the skill levels of training and reemployment occupations compared to the participants' own education. The first column shows that a near majority of the sample chose a training occupation that is comparable to their own skill level (±1 year; 49.09%); yet, overshooting is common among the TAA participants (38.99%). We also find that 11.92% of participants choose a training occupation that is below their skill level. Overall, participants train for occupations that are associated with on average 0.74 more years of education than the participant had upon entering the program. The second column shows a similar variable for reemployment occupation comparing a participant's own education level to the average education for job holders in the reemployment occupation. While 38.99% of participants overshoot to find a higher-skilled job, only 25.6% of participants succeed to in finding one.[19] 17.27% of participants actually end up with a job that is lower-skilled relative to their education. Overall, reemployment occupations are also associated with higher educational attainment than the participants' own, but the difference is smaller than that of training occupations.

[Table 2 about here]

Panel B of Table 2 summarizes the same statistics for participants with different educational backgrounds. As noted above, one noticeable trend when comparing training occupation shares to reemployment occupation shares is that the share of participants who

[19] The shares are not directly comparable as the samples for the two columns are different. The first column is based on participants that choose job training and have a valid training occupation code. The second column is based on participants who find a job after exiting the program and have a valid reemployment occupation code.

overshoot is larger than that of those who find a higher-skilled job (middle row for all columns), implying that choosing a higher-skilled occupation for job training does not always lead to employment in one. Another obvious trend we find here is that participants with lower educational attainment tend to overshoot more. It is intuitive that people with a lower skill level benefit more from skill upgrading and therefore they show a higher rate of overshooting. However, a portion of what we observe is due to the way the variables are defined. The skill level of a training occupation is measured by the average years of schooling for job holders in that occupation as reported in the CPS while a participant's skill level is measured by his/her own educational attainment. Naturally, participants' own skill levels convey a much larger variation. The amount of variation in years of schooling is similar for TAPR and CPS samples ranging from 7 years to 17 years.[20] However, we take the mean years of schooling of all job holders for the skill-level of training occupations and these mean values range from 10.5 years to 17.0 years.[21] This makes any TAA trainee below 9.5 years of schooling an overshooter. For the same reason, a highly educated TAA trainee is less likely to be identified as an overshooter.[22]

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[20] Anyone with more than a bachelor's degree is marked as having 17 years of schooling because both TAPR and CPS do not report the actual years of schooling for those with an advanced degree. They account for a very small fraction of both datasets (especially TAPR) and we do not believe curtailing the schooling to 17 years would affect the analysis in a meaningful way.

[21] See Appendix A3 for more detailed statistics on the CPS education variable and the comparison between TAPR and CPS in terms of occupation-level education measures. The appendix is available on the author's website.

[22] This does not affect our estimation results because the propensity score matching between the treated group and the comparison group requires the same years of schooling.

V. Methodology

The main question of this study is whether skill overshooting through a federal job training program improves the labor market outcomes of the trainees. As in any other ALMPs, there is a selection issue around who chooses to overshoot. Do the high ability trainees who are predisposed to positive outcomes select into overshooting? To separate the impact of selection from the impact of overshooting itself, we use a propensity score estimation to construct a comparison group for the treated (skill-overshooters) using nearest neighbor matching with replacement. This methodology reduces the selection issues around overshooting by choosing the comparison group that is similar to the treatment group in their pre-participation characteristics.[23]

Table 3 presents the propensity score estimation results for our baseline matching criteria. English proficiency and gender show a large influence on whether a trainee overshoots. Trainees who are not fluent in English have a 9.5 pps higher chance of overshooting. This is consistent with the intuition that low-skilled workers have more to gain from acquiring higher-level skill sets and thus could be compelled to overshoot. Male participants show a substantially lower rate of overshooting (13.9 pps lower). Tenure at previous employment does not affect the overshooting decision, offering support to the argument made earlier that job-specific human capital is rather irrelevant in TAA training decisions compared to general skills that are largely captured by educational attainment. The negative impact of age on the overshooting decision is as expected, but the magnitude is

[23] As discussed earlier, selection into training given participation in a certain program poses a smaller bias than selection into participation of the program itself (Andersson et al., 2013). Our selection issue is likely to be even smaller as our analysis concerns occupation choices given everyone in our sample is receiving job training from the TAA program.

surprisingly small. 10 years of age difference only makes 1 pps difference in the likelihood of overshooting. Pre-participation earnings pose a highly significant influence although the overall effect is small. A one standard deviation increase in earnings ($22,395) lowers the likelihood of overshooting by 2.22 pps. Ethnicity also seems to be an important factor suggesting that there might be cultural influences in the overshooting decision making.

[Table 3 about here]

While we have used several individual characteristics available to us in the TAPR, we may still suffer from selection bias due to unobserved qualities of the TAA trainees. Ambition is an obvious one. An ambitious individual is more likely to overshoot in her training choice and find a job. The ambitious individual is more likely to obtain higher earnings as well. Her labor market outcomes would be better than those of less ambitious trainees even without overshooting. This factor, if substantial, would yield an upward bias in our outcome estimates. Higher levels of general labor market experience, the portion of a trainee's human capital that is not captured by education, are also likely to be associated with both a higher chance of overshooting and more favorable outcomes. While this creates another upward bias in our outcome estimates, this is expected to be captured, at least partially, by the trainee's age in the propensity score estimation.

Next, we construct a comparison group by matching one overshooter to two non-overshooting trainees using matching with replacement.[24] We force this matching to have the

[24] Our estimates are completed on a common support that drops individuals that have no matches. The common support is further fine-tuned with a caliper (the distance allowed for nearest neighbors) of size 0.01 which is 0.1 standard deviations of our propensity score estimates. In the second stage of matching, we use additional restrictions to require the same state and the same education level. This trims our sample to 16,194 overshooting trainees with matches.

same years of schooling within the same state of residency.[25] Identical schooling is forced on our matches for the reason we discussed above and review here. Overshooting, as defined by equation (2), is negatively linked to one's own schooling; therefore, a trainee with less (more) schooling is more (less) likely to be identified as an overshooter.[26] Left untreated, when we move to analyzing the impacts of overshooting on labor market outcomes, the coefficients on the overshooting indicator could pick up the impacts of low educational attainment in addition to the impacts of skill overshooting.

Additionally, the same state of residency is used to minimize the impacts of cross-state differences in various aspects of the labor market on both the overshooting decision and labor market outcomes. States differ greatly in terms of industry composition and skill demands, labor force composition, and the administration of workforce development programs like the TAA. Another important factor is the difference in UI benefits across states. TAA trainees are eligible for income support during their training as an extended UI benefit. More generous UI benefits may encourage TAA participants to choose longer training programs that are more likely to be associated with higher skill-level occupations. This stronger incentive could create a downward bias in our estimates. A shorter duration of UI benefits may encourage TAA participants to enroll in any training in order to extend the benefit payments. This then could hurt the overall outcomes of the TAA training provision. If there is a tendency toward or away from overshooting, it could create a bias in the relevant direction noted. Forcing the matching

[25] Neither of these requirements are driving the results. Including state dummy variables in the propensity score estimation yields similar results and our results hold when we run our analyses on those that only have 12 years of education.

[26] A propensity score estimation with years of schooling as one of the independent variables finds one more year of schooling lowers the chance of overshooting by 21.5 percentage points.

to be of the same years of schooling and the same state of residency can eliminate these various unobservable factors that could bias our outcome estimations.

Figure 1 and Table 4 demonstrate the quality of our matching and its balance. Figure 1 displays the histogram with predicted probabilities of skill overshooting for the matched sample on top (Treated: On support)[27] and the comparison group at the bottom (Untreated). The figure displays what is near mirror images on the top and bottom suggesting considerable overlap between the two groups. Table 4 shows summary statistics for the treated and the control comparison groups after matching. The variables display similar values for these two sample groups with no mean values statistically different from each other. This table together with Figure 1 convince us that the following analyses using the propensity score matched sample is valid.[28]

[Figure 1 about here]

[Table 4 about here]

VI. Results

Before a more detailed analysis using the treated and comparison groups constructed based on the propensity score matching as described above, we first perform simple OLS estimations using all valid observations available as the following:

$$Outcome_i = \alpha + \beta\, I\_OS_i + \gamma X_i + \varepsilon_i$$

[27] This figure has small areas for those that overshot but were not matched (Treated: Off support). These areas for our pictures are hard to see because most overshooting trainees have a match.

[28] For more details on the quality of this paper's matching, see section A5 in the online appendix which is available on the author's website.

Outcome$_i$ is various labor market outcomes such as whether the worker is reemployed, the wage replacement rate, and earnings after exiting the program. We also look at whether the overshooters indeed find a job that is of a higher skill level than her own. This outcome measure takes the value 1 if the average education of job holders of the reemployment occupation is one year or more above the trainee's own education. I_OS_i is an indicator for skill overshooting defined above. X_i is a vector of control variables including education, limited English proficiency, tenure at previous employment, age, gender, and ethnicity. Additionally, we control for the CZ-level unemployment rate in the year of program exit. We also use the 2-digit SIC industry of the previous employer and exit year fixed effects.

Table 5 presents the results. Skill overshooting lowers the chance of finding a job by 2.7 pps. This suggests that aiming for a higher-skilled job through training is a risky strategy as the trainees would have to compete with better workers. However, if the trainee finds a job, they have a 43.0 pps higher chance of being at a higher-skilled job, which translates to a higher wage replacement rate (1.7 pps) and post-exit earnings ($885). That is, skill overshooting is a strategy that comes with a trade-off: higher earnings but a lower chance of reemployment.

[Table 5 about here]

a. Baseline Estimation – Skill Overshooting on Labor Market Outcomes

Now we carry out the estimation for three labor market outcome measures using the treated and control groups constructed based on propensity score matching. We use exit year fixed effects to control for factors associated with the overall business cycle at the time participants begin job searches. We also control for the unemployment rates of trainees' CZs in the year of program exit to capture the local labor market more accurately. We use dummy variables – a dummy for rates below 4%, dummies for 1 percentage point intervals between 4% and 10%, and a dummy for rates above 10% – rather than the rate as a continuous variable to allow its influence to be non-linear.

Geography is an important factor in determining people's labor market experiences. Barnette and Park (2017) show that geography influences the labor market outcomes of a TAA participant in two ways. First, the local labor market could affect the quality of service delivery at the local AJCs as their workload changes. Second, the local labor market could affect the participants' training decisions. Both influence the participant's choice of a training program that we explore in this study. More broadly, many studies show that the adverse impacts of trade-induced displacements affect all workers in the local area beyond those who are directly affected (Kondo, 2018; Park, Reynolds, & Rohlin, 2014; Autor et al., 2013). This means that TAA displacements could be linked to a worsening local labor market overall. This could create a systematic downward bias in the outcome measures.

Table 6 shows the results of our baseline analysis with all matched observations in Panel A. We find that the pattern we observed in the OLS estimation of Table 5 remains strong. Overshooting has positive impacts on earnings, but the strategy has risks since it reduces the chance of finding a job after training. The first column shows that overshooting lowers the reemployment rate by 1.9 pps with the mean rate for all observations in this estimation at 85.6%. The positive earnings impacts can be seen in both the wage replacement rate and the level of post-exit earnings. With the pre-participation earnings controlled, overshooting improves the wage replacement rate by 2.0 pps and annual earnings by $615.

[Table 6 about here]

Comparing the coefficient estimates in Table 5 and Table 6 shows the direction of influence that the selection issue has on the outcomes. Trainees who select into overshooting are associated with a lower reemployment rate (-0.027 compared to -0.019), a lower wage replacement rate (0.017 compared to 0.020), and higher post-exit earnings ($885 compared to $615). This means that the obvious factors such as education (low), gender (female), age (younger), pre-participation earnings (low) and English proficiency (limited), that we found in Table 3, cannot explain the selection bias. These factors are all associated with low levels of earnings, which should lead to a higher wage replacement rate and lower post-exit earnings. Perhaps the less obvious factors such as industries of previous employers and states of residency have a larger influence in who chooses to overshoot.

Based on the coefficient estimates in Table 6, we calculate the expected value of skill overshooting based on the mean values and the coefficient estimates of the reemployment rate and post-exit earnings as a crude way to summarize the trade-off. A non-overshooting trainee has 85.6% chance of finding a job with the mean earnings of $25,668. Therefore, the expected value of the post-TAA outcome is $21,972 for these non-overshooting trainees. The expected value for an overshooter is $21,999 from an 83.7% chance of reemployment at an average earnings of $26,283. Thus, the value of choosing to overshoot is $27, which is a 0.12% advantage. This small advantage of skill overshooting in terms of the expected value does not imply that the impacts of overshooting are negligible. Rather, it tells us that the two forces of the trade-off – the positive impacts on earnings and the negative impacts on the reemployment rate – are comparable in size. For this reason, we cannot claim with certainty that skill overshooting is a winning strategy for all TAA trainees. The trade-off should be considered individually for each participant based on their specific circumstances.

In Panel B, we look at the subsample of TAA trainees who exited the program during the years of a healthier economy (2003-2007).[29] This is a useful robustness check to see whether our findings hold across different states of the business cycle since a weak labor market has strong consequences on the labor outcomes of those changing jobs (See Oreopoulos, Von Wachter, & Heisz 2012 and Kahn 2010). The estimation results show that the trade-off between the earnings gain and the loss in reemployment rates is again well preserved, but the impacts are bigger in magnitude. The positive impact on earnings increase from $615 for this paper's baseline sample to $953 for those in the healthier economy. Somewhat surprisingly, the negative impact on the reemployment rate also increases from a 1.9 pps decline for the baseline sample to a 2.2 pps decline for the healthier economy sample. The expected values of post-exit outcomes for overshooters and non-overshooters increase to $22,655 and $22,422, respectively. So, the value of overshooting is $233, which is 1.04% advantage over non-overshooting. This implies that overshooting is a more attractive strategy when the economy is in better shape.

b. Analysis of Subsamples

In this section, we analyze various subsamples based on natural divides suggested in the literature along with previous findings within this paper. Specifically, we investigate how gender, age, local labor market characteristics, urban versus rural areas, and education levels play a role in determining the impacts of overshooting. Table 1 shows various statistics of these subsamples and shows the disparity between different types of participants: male and

[29] We use 2003-2007 as the healthier economy because broader definitions of unemployment (U-5 and U-6 from the BLS) start falling in 2003 after the recession of 2001. These indicators have sharp increases starting in 2008 due to the next recession.

female; older and younger; urban and rural; high and low education in terms of pre-participation background, program benefit utilization, and the labor market outcomes after exiting the program. This table suggests that these subsamples have fundamentally different labor market experiences and these disparities are worth exploring. For each of these subsamples, we create new matches by employing an additional matching restriction for trainees to be matched within each subsample. Table 7 presents the results for all subsamples.

[Table 7 about here]

b.1. Gender Subsamples: Men vs. Women

Panel A shows the outcome estimation for male and female trainees. Gender subsamples display the most drastic differences among the subsamples we investigate. We saw in Table 1 that male trainees receive drastically higher earnings both before and after participation despite the fact that their education level is similar to their female counterparts on average. Table 1 also demonstrates that female trainees take both job and remedial training at much higher rates. Based on the mean values of the reemployment rate and post-exit earnings, we still observe that male trainees enjoy more favorable labor market experiences. However, skill overshooting improves the outcomes of female trainees greatly. It increases the post-exit earnings by $1,143 which is 5.3% of their mean earnings ($22,198) without any significant impact on their chance of reemployment. The opposite is the case for male trainees. Overshooting hurts male trainees by lowering the reemployment rate by 3.1 pps without any significant gain in post-exit earnings. This translates to a 5.99% gain in expected value of post-exit outcomes for female overshooters and a 3.03% loss for male overshooters.[30]

b.2. Age Subsamples: Age group 43-65 vs. Age group 18-42

We split the sample in halves with participants of age 43-65 and those of age 18-42. We look at the difference in experience across age to account for two factors. First, older and younger participants make very distinctive choices during TAA program participation especially regarding training. Table 1 shows that while 76.54% of younger participants received job training, only 63.09% of older participants did. Second, job loss has larger negative consequences for older workers compared to the young. Table 1 shows that younger participants had a much easier time finding a job after exiting the program with a substantially higher wage replacement rate. These statistics go along with the general findings in the involuntary displacement literature that compared to younger workers, older workers experience a larger fall in their earnings relative to their similarly aged peers after displacement.[31]

Panel B of Table 7 shows the results for our two age groups. Overshooting shows bigger gains and smaller costs for younger trainees. The impacts on annual earnings are nearly identical for younger ($554) and older trainees ($502), but younger trainees on average enjoy a higher wage replacement rate as their pre-participation earnings are lower (Table 1). On

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[30] The expected values of post-exit outcomes are $20,024 for female overshooters and $18,891 for female non-overshooters. The values are $25,033 and $25,817 for the male counterparts, respectively.

[31] Couch and Placzek (2010) provide a summary of this work. Most studies show an initial earnings fall of less than 40% and a lasting fall of less than 20%. Chan and Stevens (2004) is the one study for workers over 49 years of age in that summary; they find an initial earnings fall of 48-50% with a lasting fall of 23-47%.

average, younger trainees experience a higher chance of reemployment (89.7% compared to 82.0% for older trainees) and the negative impact of overshooting on the reemployment rate is smaller for younger trainees (1.6 pps compared to 2.6 pps), reflecting the fact that finding a job is generally harder for older workers. However, the magnitude of these impacts is smaller than that of other subsamples. Overshooting creates a small gain (0.32%) in the expected value of post-exit outcomes for younger trainees and a small loss (1.26%) for older trainees.[32]

b.3. Geographic Subsamples: Urban vs. Rural

We also look at the differences across geography by comparing those dwelling in urban areas versus those in rural areas because displaced workers in rural areas are likely to face a lower availability of job opportunities compared to urban workers. Evidence continues to mount that rural areas experience mass job losses more frequently than urban areas (Diamond, 2016). This would not only lead to worse labor market outcomes for participants in the rural areas, it is also possible that different training choices have different impacts on these workers.

Panel C of Table 7 presents the results. We find that the labor market works in favor of urban dwellers in terms of both the chance of reemployment and earnings on average. Overshooting reverses this trend a bit. Overshooting increases the earnings of rural trainees by $1,080, making up half of the earnings differential between urban and rural trainees on average ($26,140 and $23,998, respectively). This large positive impact on earnings comes without a noticeable decline in the reemployment rate. On the other hand, the impacts of overshooting are generally negative for trainees in the urban areas. It lowers the chance of reemployment by

[32] The expected values of post-exit outcomes for overshooters and non-overshooters are $23,272 and $23,197 for younger trainees and $20,608 and $20,872 for older trainees, respectively.

1.6 pps without any significant gain in earnings. In terms of the expected value of post-exit outcomes, overshooting creates a 4.13% gain in expected value for trainees in rural areas and 1.32% loss for those in urban areas.[33] The findings on these subsamples along with the gender subsamples suggest that overshooting is especially effective in improving the labor market outcomes of particularly disadvantaged groups of workers based on pre-participation characteristics.

b.4. Education Subsamples: Less than High School vs. More than High School

Next, we analyze how the impacts of skill overshooting differ across education levels of the trainees by splitting the sample into trainees with less than a high school education (less than 12 years of schooling) and more than a high school education (more than 12 years). We exclude trainees with exactly 12 years of schooling for this analysis.

How skill overshooting would influence the labor market outcomes of these two groups is not intuitively obvious. One could predict that it would be more beneficial to lowly-educated trainees since given a lack of general skills and other marketable skills, improving their skill level would be especially valuable for reemployment. On the other hand, overshooting could be more beneficial to highly educated trainees as they have the general ability to apply the newly acquired skills more efficiently.

Panel D presents the results. We find that skill overshooting is highly beneficial for the earnings potential of trainees with higher education. It raises their post-exit earnings by $1,186. Unlike the female and rural-dwelling subsample, however, overshooting poses a

[33] The expected values of post-exit outcomes for overshooters and non-overshooters are $21,417 and $20,566 for trainees in rural areas and $22,235 and $22,533 for those in urban areas, respectively.

negative impact on the reemployment rate (-1.7 pps) for this group. We do not find any noticeable impacts on trainees with lower education but this could be due to the small sample size of this group. Both groups show gains in the expected values of post-exit outcomes. Overshooters with more than a high school education gain 2.10% and those with less than a high school education gain 1.97%.[34]

VII. Conclusion

In this paper, we investigate the role of a federal active labor market program in forming the outcomes of participants with a focus on the job training provision for the Trade Adjustment Assistance (TAA) program. Specifically, we look at the participant's choice of training occupation as a strategy to improve their earnings potential by aiming at occupations of higher skill levels (skill overshooting) compared to their own. We investigate how skill overshooting affects their reemployment rate, wage replacement rate, and earnings after exiting the program.

Among the workers entering the TAA program between 1998 and 2007, only 77% of participants find a job during the three quarters immediately following program exit and the reemployed participants recover only 87% of their previous earnings. Participants who received job training show a slightly higher rate of reemployment (80%) but their experience on earnings is nearly identical to the rest. The trainees who overshoot for a higher skill level in their training choices experience improved earnings outcomes after exiting the program although the gain comes at the cost of reduced chances for reemployment. We find that skill

[34] The expected values of post-exit outcomes for overshooters and non-overshooters are $25,159 and $24,641 for trainees with more than high school education and $19,512 and $19,134 for those with less than high school education, respectively.

overshooting increases the wage replacement rate by 2.0 pps and the annual earnings by $615, but it lowers the reemployment rate by 1.9 pps. The pattern of earnings gain with a decline in the chance of reemployment is amplified when we look at the participants who exited the program during a healthier economy (2003-2007).

Our analyses of four subsamples – female/male trainees, older/younger trainees, trainees in the urban/rural areas, and trainees with more/less than a high school education – show that skill overshooting works differently for different groups of trainees and such trade-offs disappear for certain groups of workers. We find that skill overshooting is especially beneficial for female trainees and for trainees in rural areas. Female participants show much lower earnings on average prior to participation compared to their male counterparts, but skill overshooting offers them a large improvement in their earnings ($1,443) with no discernible impact on their reemployment rate. In contrast, for men, overshooting leads to a negative impact on the reemployment rate (3.1 pps) without much gain in earnings ($173). A similar pattern holds for trainees in rural and urban areas. Participants in a rural area show drastically lower earnings prior to participation, but overshooting raises both the wage replacement rate (3.0 pps) and earnings ($1,080) without hurting their chance of reemployment. The opposite is true for trainees in urban areas. Overshooting hurts their chance of reemployment without any gain in earnings. The large gains that skill overshooting brings to female and rural trainees suggest that it is especially beneficial to workers who are traditionally disadvantaged.

Most other sample groups display the same pattern that skill overshooting improves earnings measures while it hurts their chances of reemployment. The pattern holds for trainees with more than a high school education, but the earnings gain is much larger at $1,186. Age subsamples are very similar to the baseline results except that older overshooters suffer from a larger decline in their reemployment rates.

Our findings provide an avenue to improve the outcomes of the TAA program. With a higher emphasis on the training provision compared to the other federal ALMPs, improving the performance of the TAA program likely lies within these training services. By exploring the strategy of skill overshooting in training occupation choices and its impacts on labor market outcomes of those who partake in this strategy, we provide a better understanding of the benefits with the consequences of these training program choices. Our findings on subsamples suggest that applying different strategies to participants with different backgrounds could lead to better program outcomes.

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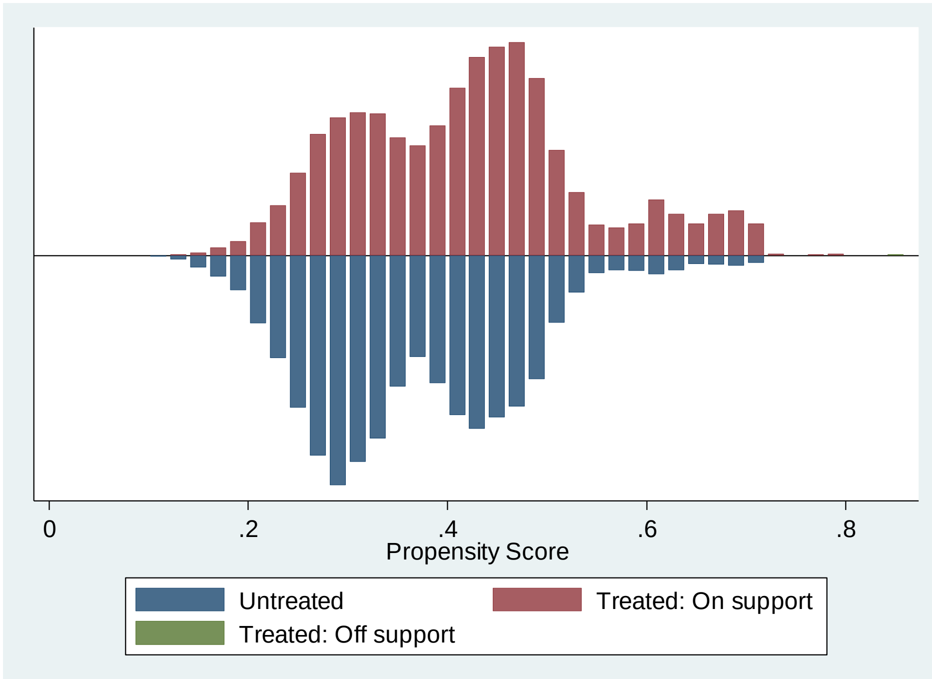
Figure 1. Predicted Probability of Skill Overshooting for Baseline Matched Sample



Note: This comes from the first part of matching for the baseline estimation of Section VI(a). *Treated: On support* is our baseline sample of those that overshoot. They are matched with two from the comparison group labeled *Untreated*. Those that overshoot but have no match are labeled *Treated: Off support*.

Table 1. Summary Statistics: Participant Characteristics and Training Enrollment

		Gender		Age		Geography		Education[i]	
	ALL	Male	Female	43-65	18-42	Urban	Rural	High	Low
Observations	320,603	156,808	160,737	153,391	118,846	133,359	35,051	82,400	41,600
A. Individual Characteristics									
Age at participation	43.88	44.06	43.68	51.52	34.02	44.48	43.09	43.32	46.35
Education (years of schooling)	12.26	12.47	12.07	12.21	12.33	12.28	12.26	14.21	9.63
Pre-participation earnings (annualized 2000 USD)	34,957	42,038	27,924	37,547	30,505	37,294	28,817	42,958	26,024
B. Training Enrollment									
a. *Received job training* (%)	65.43	63.12	67.98	63.09	76.54	63.41	60.06	72.34	46.18
Modes of job training among job trainees (%)[ii]									
- Classroom training	97.72	98.13	97.32	97.69	97.45	98.76	94.85	98.01	97.27
- On-the-job training	3.16	2.78	3.54	3.29	3.54	1.84	6.78	2.33	3.67
- Customized training	0.63	0.68	0.60	0.66	0.64	0.65	0.84	0.41	0.53
b. *Received remedial training* (%)	11.62	8.13	14.98	11.75	10.26	11.80	10.21	4.86	35.60
C. Outcomes									
a. Reemployment rate (%)									
All participants	77.20	78.06	76.47	72.75	83.62	77.42	73.79	79.68	68.64
Job trainees	80.46	80.81	80.24	76.49	84.71	80.93	79.11	81.19	75.31
b. Post-exit earnings (annualized 2000 USD)									
All participants	26,798	31,537	21,833	27,113	26,415	27,519	23,409	32,160	20,968
Job trainees	26,171	30,770	21,801	26,387	26,112	26,558	23,692	29,930	21,473
c. Wage replacement rate (%)									
All Participants	86.53	85.67	87.39	81.82	92.90	85.07	89.19	86.50	88.98
Job trainees	86.75	85.76	87.65	81.15	92.83	85.51	89.54	86.65	88.48

i. The Low Education subsample includes participants with 11 years of education or less. The High Education subsample includes participants with 13 years of education or more.

ii. The share of workers in each mode of training does not add up to 100% due to small overlaps in data.

Table 2. Summary Statistics: Skill Levels of Training and Reemployment Occupations

	a. Total Sample		b. Educational Attainment Subsamples							
	Training Occupation[i]	Reemployment Occupation[ii]	Less than HS		HS grad or eqv.		Some college		Bachelor's or more	
			Train	Reemp	Train	Reemp	Train	Reemp	Train	Reemp
Sample Share (%)										
a. Comparable to own (within +/-1 year from own schooling)	49.09	57.13	9.83	18.29	57.66	74.90	48.98	42.90	27.72	27.52
b. Higher-skilled (1+ years above own schooling)	38.99	25.60	90.17	81.71	42.33	25.01	21.03	13.94	0.00	0.00
c. Lower-skilled (1+ years below own schooling)	11.92	17.27	0.00	0.00	0.01	0.09	29.99	43.16	72.28	72.48
Obs.	93,507	55,921	9,015	5,401	54,796	30,984	24,403	15,441	5,293	4,095
Mean	0.743	.249	2.994	2.434	1.062	0.613	-0.203	-0.602	-2.029	-2.176
Std. Dev	1.635	1.592	1.531	1.441	1.089	1.015	1.291	1.273	1.345	1.441

i. Training Occupation sample (Train) includes participants who enrolled in training programs with a valid occupation code for the training occupation reported in TAPR regardless of their reemployment status. The sample shares refer to the overshooting status.

ii. Reemployment Occupation sample (Reemp) includes participants who are reemployed with a valid occupation code for the reemployment occupation reported in TAPR regardless of their training status. The sample shares refer to the status for the reemployment occupation.

Table 3. Skill Overshooting - Propensity Score Estimation: (dependent variable: *I_OS*)

Independent variables	
Limited English Proficiency	0.095***
	(0.011)
Tenure	- 3.0E-4
	(3E-4)
Pre-Participation Earnings	- 9.9E-7***
	(-1E-6)
Age at Participation	-0.001***
	(0.000)
Gender: Male	- 0.139***
	(0.005)
Eth: Black	- 0.049***
	(0.006)
Eth: Hispanic	0.100***
	(0.008)
Eth: Asian	- 0.104***
	(0.012)
Eth: Other	0.004
	(0.020)
Industry (2-digit SIC) FE	X
Participation Year	X
Obs.	53,264
Chi2	2957
Pseudo R2	0.042
Avg chance of overshooting	0.382

i. This estimation is the first part of matching. Each match is also paired with another of the same education and from the same state.
ii. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.
iii. Earnings are annualized from quarterly earnings reported in TAPR converted to 2000 USD.

Table 4. Summary Statistics: Treated vs. Comparison Group

	Mean		t-test	
Variable	Treated	Comparison	t	p>|t|
Gender: Male	.385	.387	-0.28	0.777
Pre-Participation Earnings	31,648	31,750	-0.54	0.587
Limited English Proficiency	.063	.066	-1.54	0.124
Tenure at Previous Employment	9.86	9.85	0.14	0.891
Age	42.64	42.63	0.19	0.852
Eth: Black	.152	.152	-0.02	0.984
Eth: Hispanic	.152	.153	-0.39	0.696
Eth: Asian	.024	.026	-1.26	0.206
Eth: Other	.012	.011	0.44	0.660

i. This table comes from the results of Table 3 where the dependent variable is the indicator on whether the trainee overshoots in the training relative to their education (I_OS).

Table 5. Labor Market Outcomes – OLS Estimation

	Reemployment	Higher-Skilled Reemployment	Wage Replacement	Post-Exit Earnings ($)
Overshoot (*I_OS*)	-0.027***	0.430***	0.017***	885***
	(0.003)	(0.007)	(0.004)	(148)
Industry FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Exit Year	Yes	Yes	Yes	Yes
CZ Unemp Rate at Exit	Yes	Yes	Yes	Yes
Observations	65,163	24,365	37,859	39,498
R2 (Pseudo R2)	0.073	0.372	0.222	0.233

i. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively. Standard errors in parentheses.
ii. Earnings are annualized from quarterly earnings reported in TAPR and converted to 2000 USD.
iii. We also control years of schooling, limited English proficiency, tenure at previous employment, pre-participation earnings (for wage replacement rate and post-exit earnings), age at participation, gender, and ethnicity.

Table 6. Outcome Estimation: Baseline and Healthier Economy Samples

		Wage Replacement		Post-Exit Earnings ($)	
	Reemployment	pre-participation earnings control: NO	pre-participation earnings control: YES	pre-participation earnings control: NO	pre-participation earnings control: YES
A. Baseline Sample					
I_OS	-0.019***	0.014*	0.020***	769*	615*
	(0.005)	(0.007)	(0.006)	(389)	(196)
Pre-Participation Earnings			X		X
Exit Year	X	X	X	X	X
CZ Unemp Rate at Exit	X	X	X	X	X
Mean	0.856	0.864	0.864	25,668	25,668
Obs	28,283	20,243	20,243	21,099	21,099
R2 (Pseudo R2)	0.011	0.003	0.185	0.001	0.116
B. Healthier Economy (2003-2007)					
I_OS	-0.022***	0.014	0.026***	1,228***	953***
	(0.004)	(0.012)	(0.008)	(350)	(319)
Pre-Participation Earnings			X		X
Exit Year	X	X	X	X	X
CZ Unemp Rate at Exit	X	X	X	X	X
Mean	0.865	0.869	0.869	25,921	25,921
Obs	24,842	18,085	18,085	18,856	18,856
R2 (Pseudo R2)	0.059	0.002	0.194	0.006	0.114

i. All samples use a matching restriction of the same state of residency and the same education level. The matching is performed within each sample.
ii. All estimations include a control for the CZ-level unemployment rate in the exit year and an exit year fixed effect. Both the wage replacement rate and the post-participation earnings estimations also include a control on the pre-participation earnings.
iii. Earnings are annualized from quarterly earnings reported in TAPR and converted to 2000 USD.
iv. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.
v. Robust standard errors clustered at the industry level are in parentheses.

Table 7. Outcome Estimation: Subsamples

Dependent variables	Reemployment	Wage Replacement	Post-Exit Earnings ($)	Reemployment	Wage Replacement	Post-Exit Earnings ($)
A. Gender Subsample	**a. Male**			**b. Female**		
I_OS	-0.031***	0.005	173	-0.004	0.041***	1,443***
	(0.010)	(0.008)	(411)	(0.006)	(0.006)	(273)
Mean	0.863	0.862	29,915	0.851	0.868	22,198
Obs.	12,370	9,052	9,463	15,662	11,045	11,478
R2 (Pseudo R2)	0.011	0.209	0.092	0.049	0.225	0.081
B. Age Subsample	***a. Older: Age 43-65***			***b. Younger: Age 18-42***		
I_OS	-0.026***	0.003	502**	-0.016***	0.019**	554*
	(0.009)	(0.005)	(261)	(0.006)	(0.008)	(281)
Mean	0.820	0.805	25,453	0.897	0.929	25,861
Obs.	14,597	9,730	10,259	14,021	10,878	11,193
R2 (Pseudo R2)	0.015	0.188	0.122	0.014	0.192	0.145
C. Urban-Rural Subsample	**a. Urban**			**b. Rural**		
I_OS	-0.016**	0.003	143	-0.003***	0.030	1,080*
	(0.006)	(0.008)	(412)	(0.011)	(0.023)	(559)
Mean	0.862	0.867	26,140	0.857	0.902	23,998
Obs.	14,702	10,574	11,020	3,243	2,301	2,380
R2 (Pseudo R2)	0.008	0.202	0.117	0.014	0.200	0.142
D. Education Subsample	**a. More than high school**			**b. Less than high school**		
I_OS	-0.017*	0.031***	1,186**	0.021	-0.009	-124
	(0.010)	(0.009)	(438)	(0.024)	(0.050)	(1,303)
Mean	0.863	0.869	28,553	0.831	0.888	23,025
Obs.	5,618	4,071	4,292	1,227	838	856
R2 (Pseudo R2)	0.025	0.186	0.116	0.033	0.239	0.211

i. All subsamples use a matching restriction of the same state of residency and the same education level. The matching is performed within each subgroup.
ii. All estimations include a control for the CZ-level unemployment rate in the exit year and an exit year fixed effect. Both the wage replacement rate and the post-participation earnings estimations also include a control on the pre-participation earnings.
iii. Earnings are annualized from quarterly earnings reported in TAPR and converted to 2000 USD.
iv. ***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.
v. Robust standard errors clustered at the industry level are in parentheses.