Skill and Wage Overshooting in Occupational 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. 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) or previous wage level (wage overshooting) achieve higher earnings and wage replacement rates with the cost being that it lowers their reemployment rates. Specifically, skill overshooting lowers the reemployment rates for these workers by 2.0 to 3.2 percentage points, but they enjoy an increase in their earnings by 2.0 - 2.2 percent. Wage overshooting leads to a similar decline in the reemployment rate (2.2 percentage points) but shows a much larger increase in their earnings (6.9 to 8.5%). The findings are robust to various subsamples.

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

I. Introduction

Recent labor market experiences during the Great Recession and thereafter has brought the issue of worker dislocation and reemployment into the center stage of policy discussions. The job loss rate during the Great Recession rose to 16% from more typical rates of 8-12% according to Farber (2011). The mean duration of unemployment soared to over 40 weeks in 2011 compared to an average of under 15 weeks from the 1970 to 2000.[1] Farber (2005) finds that when displaced workers become reemployed, their wages are 15% lower[2] and Farber (2011) finds that this decrease rose to 16.5% during the Great Recession. In an effort to combat these negative effects, governments around the world offer various active labor market programs (ALMPs) to dislocated workers to help with reemployment (Barnow and Smith, 2016).[3]

This paper evaluates one such program by focusing on the occupational 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 U.S. Department of Labor that is designed to help those whose employment is adversely affected by foreign competition. We use the TAA participants' data because of the information that it provides on the services each participant received as well as detailed information on the individual participants. There is a particular emphasis on the classroom occupational training in the TAA based on the idea that import competing tasks are being replaced by foreign competition at an increasing rate (Acemoglu et al., 2016; Autor, Dorn, and Hanson, 2016), rendering the skill sets possessed by the TAA eligible workers practically obsolete in the U.S. To secure a sustainable career path, obtaining new sets of skills still marketable in the U.S. is deemed necessary.

[1] Authors calculations using U.S. Bureau of Labor Statistics (2019).
[2] The sample used in this paper shows a mean wage replacement rate of 87%.
[3] Barnow and Smith (2016) give a comprehensive description of the U.S. ALMPs and a survey of the program evaluation literature on those U.S. programs. Card et al. (2010, 2015) provide a meta-analysis of ALMPs globally.

Schochet et al. (2012) show that TAA participants suffer from negative impacts on both employment and earnings in their large scale survey study of those who started receiving their UI benefits between September 2004 and October 2008. They find that the TAA trainees experience much smaller negative impacts (on both employment and earnings) compared to non-trainee participants. Our paper goes one step further into examining what type of training is most beneficial.[4]

Our investigation focuses on the participants' choice of training occupation with an intention of skill upgrading. Specifically, we examine a choice of an occupation that is beyond their skill level (overshooting) compared to a choice of an occupation that is at their skill level or below. When a participant is eligible for TAA benefits, the decision on whether to receive training is done through counseling with the staff but the choice of the occupation of training is left to the worker (Mack, 2009).[5] For this reason, the choice of training occupation reflects the participant's own intention rather than that of the counselor. 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[6] of that occupation has at least one more year of education compared to the participant.[7] *Skill upgrading* is defined as the participant finding a job in an occupation with the average job holder of that occupation having at least one more year of education.[8] To put it simply, skill overshooting concerns the training program (participant's

[4] Park (2012) is another study that looks closely at the occupational 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.

[5] Mack (2009) describes the process of the training-or-no-training decision and which training program to enter in detail from interviews with caseworkers at 44 American Job Centers (AJCs) from 23 states (Appendix B, Mack 2009). Once the training decision is made, the participant goes through a rigorous assessment to determine which training program to enter. The report says that if a participant expresses interest in a particular training program, the assessment is conducted mostly to certify the feasibility of the choice based on funding availability, personal finances, duration of training, and whether the participant has the basic skills required for the particular training program. The staff's input enters in the program choice when a participant does not know whether they want/need training or when the participant does not know which training program to enter.

[6] IPUMS CPS Data

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

[8] Admittedly, a participant's skill level would be better measured as a combination of their education and the accumulated skill sets at previous employments. Using education alone may not adequately capture their capacity to perform a certain level of tasks. However, this is less of a concern in this study because TAA participants are more likely to switch occupations as the tasks they performed at their previous employments are disappearing from the U.S. The accumulated job-related skill sets are less relevant in their reemployment in this case compared to participants in other labor market programs.

intention) and skill upgrading concerns the post-participation reemployment (participant's outcome). We also consider an alternative definition of overshooting and upgrading based on occupations which on average pay at least 25% better than the participant's previous job.

We construct the control group – TAA trainees that did not overshoot – using the nearest neighbor propensity score matching without replacement to minimize the selection bias that is inherent in any voluntary program participation. Andersson et al. (2013) documents 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. Carefully selecting a control group through propensity score matching reduces the selection issue further.

We find that overshooters succeed in finding better wages with a small cost to their employment rate. Specifically, workers who overshoot in terms of skill level in their training occupation choice increase their wage replacement rate by 1.8 – 2.9 percentage points (pps) and their earnings by 1.8 – 2.9%. But skill overshooting reduces the chance of reemployment by 2.0 – 2.3 pps. Wage overshooting increases the wage replacement by 5.3 – 9.3 pps and earnings level by 5.6 – 8.5%. The impact of wage overshooting on reemployment rate is nearly identical to that of skill overshooting at a reduction of 2.2 pps. The results are robust across different subsamples where we consider high school graduates to isolate the variance in education. We also consider workers within a Metropolitan Statistical Area (MSA) region that allows us to control for the MSA's unemployment rate in an attempt to control for demand beyond our state and year fixed effects.

The main contribution of this study is that we look more deeply at the process of workers after a layoff. As we note throughout this paper, for the past couple decades, there has been studies that look at the labor market impacts of globalization and recent studies examine the impacts of occupation- and industry-switching of the trade displaced workers. With the help of rich information on TAA services rendered to each participant, our study looks at the workers' decisions and how the decision making process influences their labor market outcomes.

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.[9] They find that workers leaving import-competing occupations face higher chances of downward switching. This could be a result of labor supply and demand shifts, but it could be driven by the conscious choices of the workers themselves. Our data on training occupations can address these choices.[10] 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.

This paper also complements previous research on the positive transitions from industrial switching behavior of the trade-displaced. Autor et al. (2014) show a positive impact of industry-switching among the trade-displaced workers in their investigation of the impacts of rising industry-level 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

[9] In section V, our alterative strategy for studying overshooting and undershooting will be directly related to their paper. There, we will discuss their paper further.
[10] Of course, the "workers' choices" could reflect that of the participant and a counselor.

manufacturing sector, experience a positive impact on their earnings. Hyman (2018) also finds positive impacts of industry-switching on earnings.[11]

Our findings can be extended to other federal dislocated worker programs that offer job training services with caution. TAA program benefits are delivered at American Job Centers (AJCs) under the Workforce Innovation and Opportunity Act (WIOA)[12], an umbrella program that delivers employment-related services covered by many federal programs such as Employment Services (Wagner-Peyser Act), Job Corps, and Welfare-to-Work. When a worker is eligible for job training under any of these programs including the TAA program, the decision making process follows the WIOA system[13]. Career counseling and assistance with training enrollment are done with WIOA staff rather than with a staff member who is specifically designated to TAA participants.[14]

The rest of the paper is organized as follows. Section II describes the data sources, section III shows the variable definitions and summary statistics on skill overshooting, section IV presents our findings. Section V shows the data and estimation results for wage overshooting. Section VI concludes.

II. Data

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

The Employment and Training Administration of the U.S. Department of Labor 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 including individual characteristics (gender, age, ethnicity, and education), pre-participation employment information (industry, tenure, and earnings), benefits received during participation (training enrollment,

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

[12] Our sample covers people who entered the program between 1999 and 2007, so the TAA benefits were delivered through the Workforce Investment Act (WIA) system which was replaced by WIOA in July 2015.

[13] The decisions involve core services, intensive services, then training.

[14] Many TAA participants are co-enrolled in WIOA. The main administrative differences would be that TAA funds are more readily available for training program as the program has a much higher emphasis on job training by design.

occupations of training, training duration, and income support received), and post-participation information (reemployment, occupation of reemployment, and earnings). The data was acquired through a Freedom of Information Act request. Our sample covers workers who participated in the TAA program from 1998 to 2007 with the year of program exit ranging from 1999 to 2008.[15] We limit the sample to manufacturing since the TAA program was initially restricted to cover manufacturing establishments that were directly hit by import competition.[16]

For the analysis controlling for the local labor market, we need information on the participant's geographic location beyond the state of residency reported in TAPR. We link the TAA petition data to TAPR using the petition numbers and use the location of the previous employer (MSA) as a proxy for the participant's location.

b. Current Population Survey (CPS)

IPUMS CPS together with TAPR data is used to construct our main variables, skill overshooting and skill upgrading. We construct skill overshooting and upgrading by comparing a participant's skill level to the average skill level for those in the occupations for which the participant is trained and the job for which the participant is employed. We use educational attainment as a proxy for skill level and the skill level of an occupation is measured as the average years of schooling for job holders of the occupation taken from the CPS file.

c. Occupational Employment Statistics (OES)

OES reports hourly wages and annual earnings for each occupation based on the Standard Occupation Code (SOC) system. We use the occupation-level earnings in constructing the wage overshooting variable by comparing a participant's wages at the previous employment to the median

[15] See Table A1 in the appendix for the distribution of the educational attainment of participants across years.

[16] The TAA program was revised in 2002 with an expanded eligibility to include non-production establishments. The expansion also included upstream and downstream establishments from the directly affected establishments without any restriction on industry. 19% of the TAA participants recorded in TAPR are from non-manufacturing sectors

earnings of his/her training occupation. The dataset is managed by the U.S. Bureau of Labor Statistics (BLS).

d. 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 MSA-level unemployment rates to control for the participant's local labor market. We offer the analysis with MSA-level unemployment rate as a robustness check as only 24% of TAA participants reside in a MSA and therefore, using local labor market information drastically reduces the sample size.

e. Trade Data

We use the updated version (v2011.3.3) of Bernard, Jensen, Schott (2006) which is publicly available on NBER. This revision extends the original data up to the period of 1972 – 2007 based on 4-digit 1987 Standard Industrial Classification (SIC) codes. We use the data from 1998 to 2007. This dataset contains raw trade data, import shares, and the import penetration rate for all trade partners and low-income partners. Low-income countries are defined to have their GDP per capita that is less than 5% of the U.S. level throughout the period between 1972 and 2005. We take the total imports from all trade partners and low-income trade partners together with the total exports of the United States and the industry-level total value of shipments in the U.S. to construct our import penetration rates.[17]

III. Definitions and Summary Statistics

a. Definitions: Skill Overshooting and Skill Upgrading

[17] We also construct the import penetration variable from China alone for use in estimations. All estimates are nearly identical to those in specifications with the low-income country import penetration and are therefore not reported in this paper.

Skill overshooting is a choice variable that captures a participant's intention as she chooses the occupation for which to be trained. It compares the skill level of the training occupation to that of the participant's skill level. Higher skill overshooting signals that the participant wants to improve her job prospects by increasing her skill level. On the other hand, *skill upgrading* is an outcome variable that is linked to reemployment. Skill upgrading compares the skill level of the reemployment occupation to the participant's skill level.

In this study, we use educational attainment measured in years of schooling as a proxy for skill levels.[18] Accordingly, skill overshooting ($Skill\_OS_i$) and skill upgrading ($Skill\_UP_i$) are defined as the following:

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

$$Skill\_UP_i = \text{Average schooling of participant } i\text{'s reemployment occupation} - i\text{'s schooling} \quad (2)$$

The information on participants' schooling is obtained from the TAPR. The average schooling of occupations of training and reemployment are measured as the average years of schooling of job holders for the occupation in the CPS.[19]

Using skill overshooting and skill upgrading defined above, we also construct indicator variables, $I\_SkillOS_i$ and $I\_SkillUP_i$, for overshooting and upgrading, respectively. We consider a two-year (±1 year) band around the participant's 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_SkillOS*. The indicator variable for skill upgrading is constructed in the same way.

$$I\_SkillOS_i = 1 \quad \text{if } Skill\_OS_i > 1; \quad 0 \text{ otherwise} \quad (3)$$

[18] The best measure of a worker's skill level would be a combination of schooling and previous work experiences. However, proper measurement of this is not a straightforward matter. Another proxy to consider is the skill level of pre-participation employment measured as the average level of education of the workers in that occupation. Unfortunately, pre-participation occupation is not reported in the TAPR. There are other worker-level data sets such as PSID, NLSY, or IPUMS CPS March Supplement that report previous and current occupations, but they lack the detailed information on job-training programs between the jobs.

[19] 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.

$$I\_SkillUP_i = 1 \quad \text{if } Skill\_UP_i > 1; \quad 0 \text{ otherwise} \tag{4}$$

Table 1 summarizes the skill overshooting and the skill upgrading variables. A near majority of the sample chose a training occupation that is comparable to their own skill level (±1 year; 49.24%). This is also the case for the occupation of reemployment (57.49%). Table 1 also shows that overshooting is common among the TAA participants. 38.94% of the sample overshoots in their training choices. However, upgrading is less common and occurs in 25.56% of the sample. We still observe participants who undershoot (11.82%) and downgrade (16.96%); however, these participants account for a small fraction of the TAA participants. Overall, participants train for jobs that have 0.74 more years of education than the participant had upon entering the program and these participants end in jobs that have 0.25 more years of education than the participant originally had.

Table 2 summarizes the pattern of overshooting and upgrading for people with different levels of educational background. The obvious trend is that participants with lower educational attainment tend to overshoot more and achieve upgrading more frequently. 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 part of what we observe in Table 2 is also due to the way the variables are defined. The skill levels of occupations of training and reemployment are measured by the average years of schooling of people who are employed in that occupation as reported in the CPS while participants' skill level is his/her own educational attainment. Naturally, participants' own skill level conveys much larger variation. The mean values of the average education for occupations from the CPS are around 13.3 years with the minimum values around 10.5 years of schooling. TAA participants' education levels vary from 8 years to 17 years.[20] This makes anyone below 9.5 years of schooling an overshooter. The same goes for highly educated participants. If you are highly educated, you will likely be sitting at the higher end of that spectrum, making you an undershooter. For this reason, the coefficient on education regarding the estimates on who overshoots and who upgrades should be interpreted with caution.

[20] See Table A1 in the Appendix for a detailed breakdown of these summary statistics.

IV. Results

The main question of this study is whether aiming for a higher skill-level occupation (skill overshooting) through a federal job training program improves the labor market outcomes of the trainees. Before a more detailed analysis, we first want to confirm whether skill overshooting leads to skill upgrading once we control for individual characteristics of TAA participants using simple OLS estimations as the following:

$$Outcome_i = \alpha + \beta\ I\_SkillOS_i + \gamma X_i + \varepsilon_i$$

$Outcome_i$ will take different values including an indicator for skill upgrading ($I\_SkillUP_i$) and various labor market outcomes such as whether the worker is reemployed, the wage replacement rate for the reemployed worker, and the earnings for the worker after exiting the program. $I\_SkillOS_i$ is an indicator for skill overshooting defined above. X_i is a vector of control variables such as education, age, gender, ethnicity, MSA residency, and the year of program exit. We also use 2-digit SIC industry and state fixed effects.

Table 3 presents the results. Skill overshooting shows a strong connection to skill upgrading. Participants who overshoot show a higher likelihood of upgrading by 41.3 pps. However, there is a cost to overshooting as these workers have a decreased reemployment rate (2.8 pps). Earnings show improvement with a higher wage replacement (1.8 pps) and higher post-participation earnings (2.2%).

a. Propensity Score Matching Estimation

A question that naturally arises here is whether the previous findings are driven by selection. Do the high ability trainees who are pre-disposed to upgrading select into overshooting? In an attempt to separate the impact of selection from the impact of overshooting itself, we construct the control group for the treated (skill-overshooters) using a propensity score via the nearest neighbor matching without replacement. This methodology reduces the selection issues around the overshooting behavior by allowing us to choose the control group that are similar to the treatment group in their pre-participation characteristics.[21] We use age, gender, educational attainment, tenure at previous employment, English proficiency, pre-participation earnings, and ethnicity along with participation year fixed effects and 2-digit SIC industry fixed effects to estimate the likelihood of overshooting.

Table 4 provides the results of the propensity score estimation. The impact of higher educational attainment is negative with large magnitudes and strong precision. Each additional year of education is associated with a decline in the likelihood of overshooting by approximately 22 pps. This finding is consistent across specifications although this is partly to be driven by the definitions of the overshooting and the upgrading variables as discussed earlier.[22] Limited English proficiency also tends to discourage participants from overshooting with the decrease in likelihood of approximately 5 pps. Older workers and those with a longer tenure at the previous job are also related to less overshooting which fits the narrative that more senior workers are less likely to dramatically change their occupation. Pre-participation earnings have positive impacts on the likelihood of overshooting where a one log point increase in pre-participation earnings leads to an increase in the likelihood of overshooting by approximately 4 pps. Since the wage rate is a good signal for the worker's skill level, a higher pre-participation earnings linked to a higher rate of skill overshooting is not surprising. In general, white females are more likely to overshoot; this is clear from the estimates on our dummy variables regarding ethnicity along with the estimates on our male dummy variable.

We also include industry-level import competition as a factor that affects the choices of training occupation. Import competition is measured by the import penetration[23] for the 3-digit SIC industry of

[21] As discussed earlier, selection into training or not given participation in a certain program poses a smaller bias than selection into the participation of the program itself (Andersson et al., 2013). Our selection issue is likely to be smaller as our analysis concerns occupation choices given everyone in our sample is receiving job training from the TAA program.

[22] We are not concerned with this issue since the interpretation of these coefficients are not of particular significance. Rather, the estimation is attempting to capture the behavioral patterns common to people with certain individual characteristics that will allow us to match similar workers. However, the results still provide us with a better understanding of who overshoots.

[23] $ImpPen_{ixt} = \frac{Imp_{xit}}{VS_{it} - Exp_{it} + Imp_{it}}$ where i = 3-digit SIC industry, t = participation year, $x \in$ {all imports, low-income imports}

their pre-participation employment. We look at two sources of import competition: one from general imports and one from imports from low-income countries. Low income countries are the countries whose per-capita GDP is 5% or less of that of the U.S. throughout the sample period following Bernard, Jensen and Schott (2006). This includes China. A higher awareness on the negative impact of foreign competition on employment could have opposing impacts on their overshooting behaviors. A worker might try harder to upgrade their skill sets, so they have better job security in the long-run (more likely to overshoot); or, a worker might become even more insecure about the chances of reemployment, so they choose an occupation with lower skill-level and/or lower pay (less likely to overshoot).

Import penetration from low-wage countries have large, positive, and significant impacts on the chance of overshooting while general imports show small and insignificant coefficients. Specifically, participants displaced from sectors with high import competition from low-income countries increase their likelihood of overshooting with their occupational training by 9.9% to 11.1%. These import measures seem to be capturing certain behavioral patterns that are not directly related to the level of education since adding import competition from low-income countries leave the results on education to be essentially the same.[24]

Given the large and significant impacts of pre-participation earnings and of import competition from low-income countries, we choose specification six to construct the control group participants. For each treated observation, one or two participants are chosen as a control group within the same state of residency. Table 5 shows summary statistics for the treated and the control groups. All five variables display very similar values for these two sample groups. This indicates that the results of the following estimations on labor market outcomes are not likely driven by these observable characteristics of participants.

[24] The coefficients of specifications V and VI are essentially the same if we use import penetration from Chinese imports only rather than all imports from low-wage countries. Chinese imports account for the majority of low-wage country imports throughout the sample period.

b. Benchmark estimation – Skill overshooting on labor market outcomes

Table 6 shows the impacts of skill overshooting on various labor market outcomes. These findings show that the overshooters enjoy more earnings although the strategy has some risks since it reduces the chance of finding a job after training, consistent with the OLS estimation shown in Table 3. The first column shows that the link between overshooting and upgrading is large and strong. Skill overshooting in training leads to a higher likelihood of skill upgrading in employment by 40.2 pps. Recall that this coefficient was 0.413 in the OLS estimation from Table 3. This suggests the selection issue is not the driving link between overshooting and upgrading. The second column of Table 6 indicates that overshooting reduces the chance of reemployment by 2 pps indicating that overshooting is not costless; overshooters are taking a risk of not being able to find a job after completing the training. The rest of Table 6 shows the earnings effects. Overshooting raises the wage replacement rate by 1.7 pps and post participation earnings by 2.2% after accounting for prior earnings.

The same overall results hold in the MSA subsample which is found in Table 6 Section B. This is one of the two subsamples that we consider for robustness. The advantage of this group is that we can control for local labor market conditions beyond the state and year fixed effects. Barnette and Park (2017) show the importance of geographic location in determining the labor market outcomes of a TAA participant in two ways . First, the local labor market situation affects the service delivery at the local AJCs as their workload changes. Second, the local labor market situation could affect the participants' training decisions. Both influence whether a participant receives occupational training and which training she receives; these are the main decisions we explore in this study. More broadly, the adverse impacts of trade-induced displacements have been shown to spread to other workers that share the same local labor market (Kondo, 2018; Park et al., 2014; Autor et al., 2013).

We employ the information on the local labor market situation by using dummies on the MSA unemployment rate upon exiting the program grouped into the following intervals: 6-9%, 9-12%, and 12% or higher. The disadvantage of this subsample is the decrease in observations. Again, we see that overshooting increases the chance of upgrading by 50.5 pps. There is still a cost of overshooting for this subsample with reemployment rates being 3.2 pps lower. The results on the wage replacement rates and earnings are very similar to what we found for the entire sample in magnitudes but are less statistically significant. This could be due to the smaller sample size.

c. Analysis of the High School Educated Subsample

To minimize the variations in participants' skill level further, we continue the analysis by holding constant the education level of the participants. Specifically, we consider participants who are high school graduates or have the equivalent level of education. They have one of the following: a high school diploma, 12 years of schooling without a diploma, or a GED. We provide the results of the propensity score estimation for this subsample in Table 7. The first three columns show the results regardless of participants' geographic location and the next three columns show the results for those who reside in a MSA. With years of schooling no longer a factor for the estimation, limited English proficiency becomes more important. In the propensity score estimation for the total sample (Table 4), limited English proficiency reduced the chance of overshooting by about 5 pps. Here, the negative impact is 8.2 pps. The impact of prior earnings for this sub-sample is still positive at 2.9 pps after restricting the sample to the same level of education. The link between higher skilled workers (signaled by higher pre-participation earnings) and higher rate of overshooting is consistent with what we find for the whole sample (Table 4) but with a smaller magnitude. The results are similar for those within MSAs.

Table 8 shows the estimation on labor market outcomes for this subsample. The estimates are very similar to those of Table 6, the outcome estimation with participants with all levels of educational attainment, although Table 8 demonstrates a bigger positive impact on the earnings outcomes. Again, overshooting comes with a trade-off, it reduces the chance of reemployment by 2.9 pps but it improves earning outcomes – 2.2 pps increase in the wage replacement rate and 2.9% increase in the earnings. The MSA subsample for this education group also reveals the same pattern as shown in panel B of Table 8 where skill overshooting lowers the chance of reemployment but improves earning outcomes. The estimates are similar in magnitude as well.

V. Alternative Strategy: Wage Overshooting and Wage Upgrading

Another way to approach the question of how participants can take advantage of federal job training provisions, is to examine whether they choose to train for occupations that offer wages that are substantially higher than that of their previous employment. In this, participants engage in wage overshooting rather than skill overshooting. While skill overshooting has a direct implication to the skill acquisition aspect of job training, wage overshooting is more straightforward as occupational wage information is more readily available to participants at the time of decision making.

For the analysis, we build wage overshooting and wage upgrading variables in the similar manner to the way we build the skill overshooting and skill upgrading variables. Wage overshooting ($Wage\_OS_i$) captures the intention of the participant. It measures the difference between the participant's own earning prior to participation to the average earnings of the training occupation of her choice. Wage upgrading ($Wage\_UP_i$) captures the outcome of training using the post-participation earnings of the participant herself compared to her pre-participation earnings.

$$Wage\_OS_i = \frac{\text{average earnings of the training occupation in the year of participation}}{\text{participant's pre-participation earning}} \tag{5}$$

$$Wage\_UP_i = \frac{\text{participant's post-participation earnings}}{\text{participant's pre-participation earning}} \tag{6}$$

The average earnings of the training occupation is taken from OES data. Notice that wage upgrading uses the participant's own post-participation earnings rather than the average earnings of the reemployment occupation. We again construct indicator variables for wage overshooting (I_WageOS) and upgrading (I_WageUP) with a threshold of a 25% increase.[25] Specifically, we have the following:

$$I\_WageOS_i = 1, \text{ if } Wage\_OS_i > 1.25; \quad 0, \text{ otherwise} \tag{7}$$

[25] We run the same wage overshooting estimations with an alternative threshold of a 50% increase. The same general results hold but it severely limits our sample size for the outcome estimations as there are fewer observations in the treated group.

$$I\_WageUP_i = 1, \text{ if } Wage\_UP_i > 1.25; \quad 0, \text{ otherwise} \tag{8}$$

This alternative strategy is related to Liu and Trefler (2019) where the worker sorting behavior is categorized as upward or downward switching using occupation-level average earnings for both pre- and post-layoff earnings rather than the worker's own earnings as in this study. Ranking occupations based on the average earnings provides a good sense of 'which job is better' at least in the earnings sense and moving to a job with higher average earning indicates a general upward mobility of the worker. Our study differs from theirs as we focus on participants' conscious choices on whether to upgrade skill-levels or earnings as a strategic move and the impacts of such choices. As a participant chooses a training occupation, their decision would be based on a comparison between their own background (e.g. their own earnings) and information about available options (employment projection and average earnings of various occupations). If she was a high earner for the occupation she was holding previously, she would like to choose an occupation that would on average offer a wage that is higher than what she was making, not what an average worker of her previous occupation was making. As this study focuses on participants' intention to improve (indicated by their overshooting behavior), using the participant's own pre-participation earning as a benchmark is more appropriate.[26]

Table 9 provides the summary statistics from overshooting/upgrading on wages. This definition of wage overshooting splits the sample more equally amongst those that overshoot versus those that do not. Specifically, we see that 32.83% of the sample overshoots for wages while 28.13% undershoot. Again, a much smaller percentage achieve wage upgrading (14.98%) while a much larger share (45.94%) downgrades. Table 10 shows that the average size of wage overshooting decreases with the educational attainment of participants, but the decline is very small especially given a large variation of wage overshooting within each education group. We see that, on average, workers train for occupations that

[26] Measuring upward switching based on average earnings of two occupations would be more relevant if one preserves his/her own percentile in earning spectrum of an occupation as he/she switches but this is unlikely. In other words, the measure in Liu and Trefler (2019) captures the ranking of occupational earnings in general while our measure is specific to the individual.

would pay them 16% more than their earlier earnings but they end with employment that pays 87% of their previous earnings.

a. Propensity Score Estimation

Table 11 shows the propensity score estimation of wage overshooting. The specifications shown here are the same as specifications II and VI for skill-overshooting propensity score estimation shown in Table 4. Comparing the estimates of Table 11 to Table 4 indicates that wage overshooters are characteristically different from skill overshooters. First, participants with higher educational attainment are more likely to overshoot on wages where higher education shows very negative impact on the chance of skill overshooting. Second, high pre-participation earnings have a strongly negative impact. This is the opposite of the finding with skill overshooting although this could be due to our definition of wage overshooting.[27] Additionally, male participants show a higher chance of wage overshooting by 14.7 pps while they are much less likely to skill-overshoot (by 14.5 pps). Being displaced from industries with high import competition from low income countries does not seem to have much of an impact on the likelihood of wage overshooting of the participant.

Yet there are characteristics that affect the chance of both skill and wage overshooting in the same direction. Participants with limited English proficiency are less likely to overshoot on both skill-level and wage implying that they are more risk averse in their reemployment efforts. White participants are more likely to overshoot in both skill and wage.

The second set of columns show the same estimations for the restricted sample of high school graduates and those with equivalent education. The coefficients are very similar to the estimates for the complete sample. One noticeable thing is that limited English proficiency has larger negative impact on

[27] As the dependent variable is constructed using the participant's earnings record, the coefficients on pre-participation earnings should be interpreted with caution. The negative sign is possibly driven by the fact that participants with high pre-participation earnings are less likely to be identified as an overshooter as the average earnings of her training occupation is less likely to be substantially (25%) higher than her pre-participation earnings. This logic is similar to why we find strongly negative coefficients on years of schooling when we consider skill overshooting behavior in Table 4. Again, as in Table 4, we are not particularly concerned with this issue as we use propensity score estimation to link between individual characteristics and the tendency to overshoot in wages.

the chance of wage overshooting for high school graduates. This pattern is consistent with the previous findings for skill overshooting (Table 7). Additionally, the findings on tenure and age are nearly the same between the various samples and these results are also nearly the same as our earlier analysis of skill overshooting. The estimations with only MSA residents do not show a large difference in coefficient estimates for both the high school graduates and the complete sample including all the education levels.

b. Labor Market Outcomes

The effects of wage overshooting on labor market outcomes are displayed in Table 12. These findings are similar to the findings from the skill overshooting analysis shown earlier (Tables 6). Wage overshooting increases the probability of wage upgrading by 6.3 pps. As is the case with skill overshooting, there is a cost in wage overshooting in that it reduces the chance of finding reemployment by 2.2 pps (2.3 pps for MSA residents).

The wage replacement rate shows a substantial increase of 6.4 pps after accounting for earnings prior to entering the TAA program. Overall earnings are also positively affected by overshooting behavior showing an increase of 6.9% when pre-participation earnings are controlled.[28] The magnitudes of the impact of wage overshooting on earning-related outcomes become even larger in the MSA subsample (7.8 pps increase in the wage replacement rate and 8.5% increase in the level of earnings). Given that the average wage replacement rate is about 87% for TAA program participants, these impacts are substantial. Compared to the analysis of skill overshooting, the magnitudes on the return to wage-related outcomes are much stronger with wage overshooting.

[28] The coefficients on the wage replacement rate and earnings differ based on whether pre-participation earning is controlled because pre-participation earnings is an important factor determining both the wage replacement rate and post-participation earnings. First, participants with high pre-participation earnings are not likely to be identified as a wage-overshooter and they are also likely to have a low wage replacement rate. This creates an upward bias on the impact of wage overshooting on the wage replacement rate. Controlling for pre-participation earnings reduces the coefficient estimate on overshooting as we see in Table 12. Second, participants with high pre-participation earnings are likely to have higher post-participation earnings in general while they are less likely to be identified as an overshooter. This generates a downward bias on the impact of overshooting on earnings, so controlling for pre-participation earnings increases the coefficient estimate of wage overshooting, again, as can be seen in Table 12.

Table 13 shows the estimation results for the subsample of high school graduates and those with equivalent education. The findings in this table confirm the findings for the sample with all education levels shown in Table 12. The trainees who overshoot for wages succeed in wage upgrading with a 6.7 pps higher probability, but wage overshooting decreases the chance of reemployment by 3.3pps. Wage replacement rates for wage overshooters are 5.3 pps higher and their earnings are 6.0% higher. The results for MSA residents are very similar to the sample with no geographical restriction.

VI. Conclusion

In this paper, we investigate the role of a federal active labor market program in forming the outcomes of the participants with the focus on the job training provision of 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) or higher earnings levels (wage overshooting) compared to their own.

While the average worker entering the TAA program loses 13% of their wages, which is in line with findings for displaced workers in the literature, the participants who overshoot both for higher skill level and for higher earnings experience improved earnings outcomes after exiting the program although such improved earning outcomes come at a cost of a reduced chance of reemployment. We find that skill overshooting increases the wage replacement rate by 1.7 – 2.0 pps and the level of earnings by 2.0 – 2.2%. Workers who overshoot for wages increase their wage replacement rates by 6.4 – 7.8 pps while increasing their overall earnings by 6.9 – 8.5%. There is a cost to this behavior since these workers have their employment rate reduced by 2.0 – 3.2 pps depending on which type of overshooting is attempted. These findings are robust to various subsamples.

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Table 1. Summary Statistics: Skill Overshooting and Upgrading

	a. TOTAL SAMPLE		b. BALANCED SAMPLE[iii]	
	Overshoot[i]	Upgrade[ii]	Overshoot	Upgrade
Observations	80,749	48,704	30,812	30,812
Sample Share I (%)				
Less than -4	0.46	0.93	0.58	0.83
Between -4 and -3	1.25	1.91	1.52	1.89
Between -3 and -2	2.89	4.42	3.38	4.49
Between -2 and -1	7.22	9.68	8.17	9.83
Between -1 and 0	18.19	26.79	19.60	25.73
Between 0 and 1	31.05	30.71	31.34	31.01
Between 1 and 2	18.67	13.09	17.37	13.59
Between 2 and 3	10.62	6.22	9.67	6.11
Between 3 and 4	6.57	4.49	5.99	4.72
More than 4	3.08	1.76	2.39	1.80
Sample Share II (%)				
Overshooting / upgrading	38.94	25.56	35.42	26.22
Appropriate	49.24	57.49	50.93	56.73
Undershooting / Downgrading	11.82	16.96	13.64	17.06
Other Stats				
Mean	0.74	0.25	0.60	0.27
Std. Dev	1.64	1.59	1.63	1.59
Min	-5.74	-5.56	-5.40	-5.56
Max	9.55	8.75	9.55	8.55

i. The overshoot column for the total sample includes participants who enrolled in training programs with a valid occupation code for the training occupation reported in TAPR regardless of their reemployment status.
ii. The upgrade column for the total sample includes participants who are reemployed with a valid occupation code for the reemployment occupation reported in TAPR regardless of their training status.
iii. This is a unified sample of those who enrolled in training with a valid training occupation code then were reemployed with a valid reemployment occupation code.

Table 2. Educational Attainment and Skill Overshooting/Upgrading

	Skill Overshooting				Skill Upgrading			
	All observations[i]		Balanced Sample[ii]		All observations[iii]		Balanced Sample	
Degree attainment	No. of Obs.	Avg. Overshoot (std dev)	No. of Obs.	Avg. Overshoot (std dev)	No. of Obs.	Avg. Upgrading (std dev)	No. of Obs.	Avg. Upgrading (std dev)
Less than HS	7,827	3.01 (1.54)	2,475	2.82 (1.57)	4,796	2.43 (1.44)	2,475	2.55 (1.51)
HS grad or eqv	47,433	1.05 (1.09)	17,185	1.03 (1.11)	27,204	0.60 (1.01)	17,185	0.68 (1.04)
Some College	20,988	-0.21 (1.29)	9,060	-0.22 (1.28)	13,226	-0.61 (1.27)	9,060	-0.56 (1.28)
Bachelor	3,807	-1.92 (1.30)	1,788	-1.90 (1.33)	2,926	-2.11 (1.41)	1,788	-2.09 (1.41)
Grad School	694	-2.78 (1.34)	304	-2.78 (1.34)	552	-2.85 (1.42)	304	-2.91 (1.40)
ALL	80,749	0.74 (1.64)	30,812	0.60 (1.63)	48,704	0.25 (1.59)	30,812	0.27 (1.59)

i. Participants who enrolled in training programs with a valid training occupation code reported in TAPR regardless of their reemployment status.
ii. Participants who enrolled in training with a valid training occupation code then were reemployed with a valid reemployment occupation code.
iii. Participants who were reemployed with a valid reemployment occupation code reported in TAPR regardless of their training status.

Table 3. Labor Market Outcomes of Skill Overshooting – Benchmark (OLS) Estimation

	Chance of Upgrading		Reemployment			Wage Replacement Rate		Post-participation Earning	
I_SkillOS		0.413***		-0.028***			0.018***		0.022***
		(0.007)		(0.003)			(0.004)		(0.005)
Ed: Years of Schooling	-0.150***	-0.089***	0.006***	0.002		0.026***	0.029***	0.032***	0.035***
	(0.003)	(0.003)	(0.001)	(0.001)		(0.001)	(0.001)	(0.002)	(0.002)
Limited English proficiency	-0.052***	-0.028	-0.027***	-0.028***		-0.016	-0.015	-0.032**	-0.031**
	(0.014)	(0.015)	(0.007)	(0.007)		(0.009)	(0.009)	(0.011)	(0.011)
Tenure	0.001*	0.001***	0.000	0.000		-0.001**	-0.001**	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Log(Pre-Part Earning)						-0.473***	-0.474***	0.304***	0.303***
						(0.005)	(0.005)	(0.005)	(0.005)
Age at participation	-0.001***	0.000	-0.006***	-0.006***		-0.003***	-0.003***	-0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Gender: Male	-0.099***	-0.057***	0.006*	0.003		0.130***	0.133***	0.178***	0.181***
	(0.006)	(0.006)	(0.003)	(0.003)		(0.004)	(0.004)	(0.004)	(0.005)
Eth: Black	-0.046***	-0.048***	0.011**	0.010**		-0.029***	-0.029***	-0.049***	-0.048***
	(0.008)	(0.007)	(0.004)	(0.004)		(0.005)	(0.005)	(0.006)	(0.006)
Eth: Hispanic	-0.014	-0.014	-0.013*	-0.014*		-0.074***	-0.074***	-0.087***	-0.086***
	(0.012)	(0.012)	(0.006)	(0.006)		(0.008)	(0.008)	(0.009)	(0.009)
Eth: Asian	-0.049***	-0.033*	-0.034***	-0.036***		-0.001	-0.001	-0.016	-0.017
	(0.013)	(0.014)	(0.009)	(0.009)		(0.010)	(0.010)	(0.012)	(0.012)
Eth: others	-0.024	-0.010	-0.017	-0.018		-0.004	-0.004	-0.004	-0.003
	(0.018)	(0.019)	(0.013)	(0.013)		(0.016)	(0.016)	(0.019)	(0.019)
MSA resident	0.010	0.009	0.011***	0.012***		-0.003	-0.004	-0.003	-0.002
	(0.008)	(0.008)	(0.003)	(0.003)		(0.004)	(0.004)	(0.005)	(0.005)
constant						4.976***	4.943***	5.807***	5.766***
						(0.096)	(0.096)	(0.113)	(0.113)
Industry FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Exit Year	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Obs	26,082	26,082	66,535	66,535	*Obs*	39,823	39,823	41,572	41,572
chi2	5,967.3	10,546.4	3,792.6	3,873.3	*R2*	0.285	0.285	0.293	0.293
Pseudo R2	0.202	0.356	0.067	0.068	*Adj R2*	0.283	0.284	0.291	0.292

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table 4. Skill Overshooting - Propensity Score Estimation: (dependent variable: *I_SkillOS*)

	I	II	III	IV	V	VI
Ed: Years of schooling	-0.215***	-0.217***	-0.215***	-0.217***	-0.215***	-0.217***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Limited English Proficiency	-0.051***	-0.049***	-0.052***	-0.050***	-0.052***	-0.050***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Tenure	-0.001***	-0.002***	-0.001***	-0.002***	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log (Pre-Part Earnings)		0.041***		0.041***		0.042***
		(0.000)		(0.000)		(0.000)
Import Penetration: *All Imports*			0.023	0.026		
			(0.000)	(0.000)		
Import Penetration: *Low Income*					0.099**	0.111***
					(0.000)	(0.000)
Age at Participation	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Gender: Male	-0.136***	-0.145***	-0.136***	-0.145***	-0.136***	-0.145***
	(0.005)	-(0.005)	-(0.005)	-(0.005)	-(0.005)	-(0.005)
Eth: Black	-0.035***	-0.032***	-0.035***	-0.032***	-0.035***	-0.033***
	(0.007)	-(0.007)	-(0.007)	-(0.007)	-(0.007)	-(0.007)
Eth: Hispanic	-0.034***	-0.030**	-0.034***	-0.031**	-0.033**	-0.029**
	(0.010)	-(0.010)	-(0.010)	-(0.010)	-(0.010)	-(0.010)
Eth: Asian	-0.079***	-0.079***	-0.079***	-0.079***	-0.079***	-0.079***
	(0.013)	-(0.013)	-(0.013)	-(0.013)	-(0.013)	-(0.013)
Eth: Other	-0.031	-0.030	-0.031	-0.030	-0.032	-0.031
	(0.020)	-(0.020)	-(0.020)	-(0.020)	-(0.020)	-(0.020)
MSA resident	0.006	0.005	0.005	0.005	0.005	0.005
	(0.006)	-(0.006)	-(0.006)	-(0.006)	-(0.006)	-(0.006)
Industry (2-digit SIC) FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Participation Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	50,324	50,324	50,324	50,324	50,324	50,324
Chi2	17,315.7	17,348.7	17,318.0	17,351.5	17,338.5	17,374.8
Pseudo R2	0.251	0.251	0.251	0.251	0.251	0.252
Avg chance of overshooting	0.449	0.446	0.447	0.444	0.447	0.444

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table 5. Summary Statistics: Treated vs. Controls

	All			Matched with one control			Matched with two controls		
	Treated	Control	Total	Treated	Control	Total	Treated	Control	Total
Ed: Years of schooling	12.258	12.309	12.288	12.130	12.133	12.132	12.483	12.463	12.470
	(0.722)	(0.743)	(0.735)	(0.623)	(0.592)	(0.608)	(0.821)	(0.824)	(0.823)
Limited English Proficiency	0.032	0.036	0.034	0.035	0.036	0.035	0.027	0.036	0.033
	(0.176)	(0.186)	(0.182)	(0.183)	(0.186)	(0.184)	(0.163)	(0.186)	(0.179)
Tenure	10.193	10.235	10.217	9.891	9.824	9.857	10.721	10.595	10.637
	(8.754)	(8.809)	(8.786)	(8.529)	(8.612)	(8.570)	(9.112)	(8.964)	(9.013)
log(Pre-Part Earnings)	42.927	43.119	43.038	42.628	42.726	42.677	43.451	43.463	43.459
	(10.099)	(9.750)	(9.899)	(10.062)	(9.741)	(9.902)	(10.143)	(9.746)	(9.879)
Age at Participation	8.969	8.976	8.973	8.953	8.962	8.958	8.998	8.988	8.992
	(0.525)	(0.523)	(0.524)	(0.525)	(0.518)	(0.522)	(0.524)	(0.527)	(0.526)
Gender: Male	0.470	0.497	0.485	0.438	0.450	0.444	0.525	0.537	0.533
	(0.499)	(0.500)	(0.500)	(0.496)	(0.498)	(0.497)	(0.499)	(0.499)	(0.499)
Obs.	6,644	9,060	15,704	4,228	4,228	8,456	2,416	4,832	7,248

[*] This table of treated and control come from propensity matching based on specification VI from Table 4 where the dependent variable is the indicator on whether the trainee overshoot in the training relative to their education (I_SkillOS).

Table 6. Skill Overshooting - Outcomes: All Education Levels

A. All observations

	Upgrading	Reemployment		Wage Replacement		Post-participation Earnings	
I_SkillOS	0.402***	-0.020***		0.018**	0.017**	0.018*	0.022***
	(0.009)	(0.005)		(0.006)	(0.005)	(0.007)	(0.007)
log (Pre-Part Earnings)					-0.384***		0.410***
					(0.006)		(0.007)
Constant				1.013***	4.290***	8.455***	4.934***
				(0.089)	(0.096)	(0.089)	(0.105)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	9,136	24,106	*Obs*	17,366	17,366	18,120	18,120
Pseudo R2	0.189	0.008	*R2*	0.002	0.227	0.014	0.195
mfx	0.223	0.861	*Adj R2*	0.001	0.227	0.014	0.195

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement		Post-participation Earnings	
I_SkillOS	0.505***	-0.032***		0.017	0.020	0.022	0.020
	(0.021)	(0.010)		(0.012)	(0.011)	(0.014)	(0.013)
log (Pre-Part Earnings)					-0.434***		0.330***
					(0.013)		(0.015)
Exit Yr UR 6-9%	-0.036	-0.016		0.023	-0.007	-0.022	0.008
	(0.027)	(0.011)		(0.016)	(0.013)	(0.016)	(0.016)
Exit Yr UR 9-12%	-0.064	-0.021		0.098***	-0.069**	-0.232***	-0.102***
	(0.055)	(0.019)		(0.024)	(0.021)	(0.028)	(0.026)
Exit Yr UR 12% higher	0.231	-0.029		0.080	-0.185***	-0.432***	-0.227***
	(0.225)	(0.039)		(0.045)	(0.041)	(0.050)	(0.050)
Constant				0.827***	4.647***	8.506***	5.601***
				(0.127)	(0.156)	(0.149)	(0.183)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	1,650	5,513	Obs	3,998	3,998	4,185	4,185
Pseudo R2	0.251	0.020	R2	0.013	0.268	0.044	0.163
mfx	0.258	0.861	Adj R2	0.01	0.266	0.042	0.161

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table 7. Propensity Score Estimation: High School Grad + Equivalent

	All Geographic Units			MSA Residents Only		
	I	II	III	I	II	III
Limited English Proficiency	-0.081***	-0.081***	-0.082***	-0.129***	-0.127***	-0.126***
	(0.021)	(0.021)	(0.021)	(0.038)	(0.038)	(0.038)
Tenure	-0.002***	-0.002***	-0.002***	-0.002*	-0.002*	-0.002*
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
log (Pre-Part Earnings)	0.027**	0.027**	0.029***	0.029	0.028	0.030
	(0.009)	(0.009)	(0.009)	(0.018)	(0.018)	(0.018)
Import Penetration:		0.001			0.068	
All Imports		(0.021)			(0.049)	
Import Penetration:			0.120**			0.145
Low Income			(0.045)			(0.101)
Age at Participation	-0.002***	-0.002***	-0.002***	-0.002**	-0.002**	-0.002**
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Gender: Male	-0.148***	-0.148***	-0.147***	-0.130***	-0.129***	-0.128***
	(0.008)	(0.008)	(0.008)	(0.015)	(0.015)	(0.015)
Eth: Black	-0.028**	-0.028**	-0.029**	-0.050*	-0.051*	-0.050*
	(0.011)	(0.011)	(0.011)	(0.022)	(0.022)	(0.022)
Eth: Hispanic	-0.050**	-0.050**	-0.049**	-0.045	-0.043	-0.043
	(0.016)	(0.016)	(0.016)	(0.035)	(0.035)	(0.035)
Eth: Asian	-0.085***	-0.085***	-0.086***	-0.115**	-0.115**	-0.116**
	(0.023)	(0.023)	(0.023)	(0.043)	(0.043)	(0.043)
Eth: Other	0.010	0.010	0.010	-0.063	-0.064	-0.062
	(0.033)	(0.033)	(0.033)	(0.057)	(0.057)	(0.057)
MSA resident	-0.003	-0.003	-0.003			
	(0.009)	(0.009)	(0.009)			
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Participation Year	Yes	Yes	Yes	Yes	Yes	Yes
Obs	19,156	19,156	19,156	4,582	4,582	4,582
Pseudo R2	1,640.6	1,640.6	1,647.7	542.6	544.5	544.6
mfx	0.066	0.066	0.066	0.092	0.092	0.092

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table 8. Skill Overshooting - Labor Market Outcomes: High School Graduates & Equivalent

A. All observations

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_SkillOS	0.396***	-0.029***		0.023**	0.022***	0.026**	0.029***
	(0.011)	(0.005)		(0.007)	(0.006)	(0.008)	(0.008)
log (Pre-Part Earnings)					-0.401***		0.396***
					(0.007)		(0.009)
Constant				0.954***	4.415***	8.452***	5.037***
				(0.116)	(0.118)	(0.117)	(0.136)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	6,209	17,209	*Obs*	12,392	12,392	12,915	12,915
Pseudo R2	0.184	0.006	*R2*	0.003	0.244	0.013	0.187
mfx	0.226	0.860	*Adj R2*	0.002	0.243	0.013	0.187

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_SkillOS	0.508***	-0.023**		0.029*	0.020	0.017	0.025
	(0.027)	(0.011)		(0.015)	(0.013)	(0.017)	(0.016)
log (Pre-Part Earnings)					-0.426***		0.353***
					(0.016)		(0.018)
Exit Yr UR 6-9%	-0.067*	-0.025*		0.006	-0.023	-0.045*	-0.014
	(0.034)	(0.014)		(0.018)	(0.015)	(0.020)	(0.019)
Exit Yr UR 9-12%	-0.043	-0.051**		0.073**	-0.109***	-0.300***	-0.144***
	(0.069)	(0.026)		(0.028)	(0.026)	(0.033)	(0.031)
Exit Yr UR 12% higher		-0.062		0.034	-0.234***	-0.518***	-0.296***
		(0.048)		(0.055)	(0.051)	(0.062)	(0.061)
Constant				0.849***	4.611***	8.546***	5.430***
				(0.142)	(0.181)	(0.167)	(0.213)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	1,078	3,913	*Obs*	2,858	2,858	2,986	2,986
Pseudo R2	0.248	0.010	*R2*	0.011	0.247	0.055	0.181
mfx	0.277	0.859	*Adj R2*	0.007	0.244	0.052	0.178

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table 9. Wage Overshooting/Upgrading - Summary Statistics

	a. TOTAL SAMPLE		b. BALANCED SAMPLE[iii]	
	Overshoot[i]	Upgrade[ii]	Overshoot	Upgrade
Observations	67,005	166,241	50,247	50,247
Sample Share I (%)				
Below 50%	9.21	19.1	9.45	19.11
between 50% and 75%	18.92	26.84	19.53	27.31
between 75% and 100%	21.85	24.35	22.29	24.25
between 100% and 125%	17.19	14.73	17.1	14.2
between 125% and 150%	11.4	7.07	11.16	6.9
over 150%	21.43	7.91	20.47	8.24
Sample Share II (%)				
Overshooting / upgrading	32.83	14.98	31.64	15.14
Neither (between 75% and 125%)	39.04	39.08	39.39	38.45
Undershooting / Downgrading	28.13	45.94	28.98	46.41
Other Stats				
Mean	1.16	0.87	1.14	0.87
Std. Dev	0.71	0.50	0.69	0.50
Min	0.08	0.04	0.08	0.05
Max	11.81	16.88	11.81	16.88

i. The overshoot column for the total sample includes participants who enrolled in training programs with a valid occupation code for the training occupation reported in TAPR regardless of their reemployment status.
ii. The upgrade column for the total sample includes participants who are reemployed with a valid occupation code for the reemployment occupation reported in TAPR regardless of their training status.
iii. This is a unified sample of those who enrolled in training with a valid training occupation code then were reemployed with a valid reemployment occupation code.

Table 10. Educational Attainment and Wage Overshooting/Upgrading

	Wage Overshooting				Wage Upgrading			
	All observations[i]		Balanced Sample[ii]		All observations[iii]		Balanced Sample	
Degree attainment	No. of Obs.	Avg. Overshoot (std dev)	No. of Obs.	Avg. Overshoot (std dev)	No. of Obs.	Avg. Upgrading (std dev)	No. of Obs.	Avg. Upgrading (std dev)
Less than HS	7,220	1.20 (0.60)	4,811	1.17 (0.60)	18,783	0.90 (0.48)	4,811	0.88 (0.44)
HS grad or eqv	39,571	1.17 (0.71)	29,916	1.14 (0.69)	103,793	0.86 (0.48)	29,916	0.87 (0.48)
Some College	16,717	1.17 (0.75)	12,952	1.16 (0.75)	34,529	0.87 (0.54)	12,952	0.88 (0.55)
Bachelor	2,974	1.04 (0.66)	2,198	1.04 (0.65)	7,414	0.86 (0.52)	2,198	0.85 (0.52)
Grad School	523	1.03 (0.78)	370	1.06 (0.81)	1,722	0.87 (0.54)	370	0.85 (0.59)
ALL	67,005	1.16 (0.71)	50,247	1.15 (0.70)	166,241	0.87 (0.50)	50,247	0.87 (0.50)

i. Participants who enrolled in training programs with a valid training occupation code reported in TAPR regardless of their reemployment status.
ii. Participants who enrolled in training with a valid training occupation code then were reemployed with valid post-participation earnings reported.
iii. Participants who were reemployed with a valid post-participation earnings reported in TAPR regardless of their training status.

Table 11. Wage Overshooting – Propensity Score Estimation

	All Education levels				HS Grad +Equivalent			
	All Observations		MSA Only		All Observations		MSA Only	
Ed: Years of schooling	0.039***	0.039***	0.033***	0.033***				
	(0.002)	(0.002)	(0.003)	(0.003)				
Limited English	-0.058***	-0.058***	-0.059***	-0.059***	-0.076***	-0.076***	-0.069**	-0.068**
	(0.009)	(0.009)	(0.018)	(0.018)	(0.013)	(0.013)	(0.024)	(0.024)
Tenure	-0.001*	-0.001*	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
log(Pre-Part Earnings)	-0.820***	-0.820***	-0.873***	-0.873***	-0.856***	-0.855***	-0.826***	-0.825***
	(0.008)	(0.008)	(0.017)	(0.017)	(0.010)	(0.010)	(0.021)	(0.021)
Import Penetration:		0.007		0.059		0.057		0.076
Low Income		(0.026)		(0.067)		(0.034)		(0.082)
Age at Participation	-0.002***	-0.002***	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Male	0.147***	0.147***	0.120***	0.121***	0.146***	0.147***	0.106***	0.107***
	(0.005)	(0.005)	(0.010)	(0.010)	(0.007)	(0.007)	(0.013)	(0.013)
Eth: Black	-0.045***	-0.045***	-0.040**	-0.040**	-0.050***	-0.050***	-0.029	-0.030
	(0.006)	(0.006)	(0.013)	(0.013)	(0.007)	(0.007)	(0.016)	(0.016)
Eth: Hispanic	-0.015	-0.015	-0.026	-0.025	-0.007	-0.007	-0.027	-0.026
	(0.010)	(0.010)	(0.022)	(0.022)	(0.014)	(0.014)	(0.027)	(0.027)
Eth: Asian	-0.049***	-0.049***	-0.090***	-0.090***	-0.035	-0.035	-0.085**	-0.085**
	(0.012)	(0.012)	(0.024)	(0.024)	(0.019)	(0.019)	(0.030)	(0.030)
Eth: Other	-0.058***	-0.058***	-0.090*	-0.090*	-0.061**	-0.062**	-0.072	-0.071
	(0.016)	(0.016)	(0.036)	(0.036)	(0.021)	(0.021)	(0.048)	(0.048)
MSA resident	0.010	0.010			0.011	0.011		
	(0.006)	(0.006)			(0.008)	(0.008)		
State	YES	YES	YES	YES	YES	YES	YES	YES
2-digit SIC	YES	YES	YES	YES	YES	YES	YES	YES
Participation Year	YES	YES	YES	YES	YES	YES	YES	YES
Obs.	49,643	49,643	11,634	11,634	28,998	28,998	6,782	6,782
Chi2	24,259.0	24,259.1	6,078.3	6,079.1	14,475.0	14,477.8	3,372.3	3,373.1
Pseudo R2	0.390	0.390	0.410	0.410	0.397	0.398	0.402	0.402
Avg chance of overshooting	0.337	0.324	0.350	0.338	0.337	0.325	0.326	0.313

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table 12. Wage Overshooting - Outcomes: All Education Levels

A. All observations

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.063***	-0.022***		0.076***	0.064***	0.037***	0.069***
	(0.007)	(0.006)		(0.006)	(0.006)	(0.008)	(0.007)
log (Pre-Part Earnings)					-0.249***		0.649***
					(0.011)		(0.012)
Constant				0.831***	3.034***	8.591***	2.842***
				(0.020)	(0.095)	(0.025)	(0.111)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	12,165	16,342	*Obs*	12,036	12,036	12,165	12,165
Pseudo R2	0.011	0.004	*R2*	0.013	0.06	0.006	0.207
mfx	0.144	0.860	*Adj R2*	0.013	0.059	0.005	0.206

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.058***	-0.023**		0.093***	0.078***	0.055***	0.085***
	(0.013)	(0.011)		(0.014)	(0.014)	(0.016)	(0.015)
log (Pre-Part Earnings)					-0.307***		0.576***
					(0.023)		(0.026)
Exit Yr UR 6-9%	-0.010	-0.020		-0.013	-0.024	-0.045*	-0.024
	(0.016)	(0.014)		(0.017)	(0.016)	(0.019)	(0.018)
Exit Yr UR 9-12%	-0.005	-0.019		-0.013	-0.093***	-0.259***	-0.110***
	(0.022)	(0.021)		(0.025)	(0.024)	(0.029)	(0.027)
Exit Yr UR 12% higher	-0.066*	-0.070		-0.041	-0.185***	-0.492***	-0.222***
	(0.038)	(0.052)		(0.049)	(0.048)	(0.058)	(0.055)
Constant				0.802***	3.565***	8.688***	3.508***
				(0.030)	(0.206)	(0.053)	(0.236)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	2,861	3,775	*Obs*	2,832	2,832	2,861	2,861
Pseudo R2	0.018	0.011	*R2*	0.024	0.085	0.053	0.198
mfx	0.127	0.869	*Adj R2*	0.02	0.082	0.049	0.195

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table 13. Wage Overshooting - Outcomes: High School Graduates & Equivalent

A. All observations

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.067***	-0.033***		0.072***	0.053***	0.027**	0.060***
	(0.009)	(0.007)		(0.009)	(0.009)	(0.010)	(0.010)
log (Pre-Part Earnings)					-0.331***		0.560***
					(0.014)		(0.017)
Constant				0.832***	3.769***	8.615***	3.646***
				(0.022)	(0.128)	(0.029)	(0.154)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	6,998	9,362	*Obs*	6,922	6,922	6,998	6,998
Pseudo R2	0.013	0.008	*R2*	0.012	0.083	0.005	0.146
mfx	0.141	0.865	*Adj_R2*	0.011	0.082	0.004	0.145

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.048***	-0.029*		0.074***	0.056**	0.027	0.056**
	(0.017)	(0.015)		(0.018)	(0.017)	(0.021)	(0.020)
log (Pre-Part Earnings)					-0.347***		0.541***
					(0.027)		(0.032)
Exit Yr UR 6-9%	0.019	-0.031*		0.000	-0.015	-0.038	-0.013
	(0.019)	(0.018)		(0.021)	(0.019)	(0.023)	(0.021)
Exit Yr UR 9-12%	-0.002	-0.072**		0.009	-0.065*	-0.169***	-0.053
	(0.031)	(0.031)		(0.033)	(0.031)	(0.037)	(0.035)
Exit Yr UR 12% higher	-0.093**	-0.098		-0.124*	-0.283***	-0.567***	-0.317***
	(0.037)	(0.072)		(0.059)	(0.062)	(0.079)	(0.073)
Constant				0.782***	3.900***	8.674***	3.814***
				(0.041)	(0.247)	(0.062)	(0.292)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	1,664	2,178	*Obs*	1,649	1,649	1,664	1,664
Pseudo R2	0.016	0.014	*R2*	0.016	0.093	0.033	0.165
mfx	0.125	0.878	*Adj R2*	0.01	0.087	0.027	0.16

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1. Summary Statistics of Average Education level of each occupation – IPUMS CPS

Percentile	2003	2004	2005	2006	2007	2008	2009	2010	TAPR
1%	10.96	10.90	10.90	10.89	10.95	10.97	11.02	11.09	8
5%	11.33	11.30	11.36	11.37	11.37	11.43	11.49	11.47	9
10%	11.58	11.61	11.59	11.64	11.65	11.74	11.72	11.76	11
25%	12.10	12.13	12.12	12.10	12.13	12.20	12.17	12.22	12
50%	12.91	12.93	12.91	12.93	12.98	13.01	13.01	13.05	12
75%	14.36	14.37	14.33	14.36	14.36	14.39	14.42	14.48	13
90%	15.61	15.67	15.62	15.66	15.69	15.60	15.75	15.70	14
95%	16.24	16.22	16.17	16.22	16.21	16.10	16.25	16.24	16
99%	16.95	16.97	16.97	16.98	16.98	16.82	16.96	16.91	17
Obs	478	478	470	470	470	470	470	466	233,687
Mean	13.30	13.32	13.30	13.31	13.33	13.36	13.39	13.42	12.29
Std. Dev.	1.52	1.52	1.52	1.52	1.52	1.47	1.50	1.49	1.57
Min	10.35	10.5	10.41	10.37	10.26	10.51	10.24	10.4	7
Max	17	17	16.99	16.99	17	16.84	16.99	16.98	17

Table A2. Skill Overshooting - Outcomes: All Education Levels

A. All observations

	Upgrading	Reemployment		Wage Replacement		Post-participation Earnings	
I_SkillOS	0.402***	-0.02***		0.018**	0.017**	0.018*	0.022***
	(0.009)	(0.005)		(0.006)	(0.005)	(0.007)	(0.007)
log (Pre-Part Earnings)					-0.384***		0.410***
					(0.006)		(0.007)
Constant				1.013***	4.290***	8.455***	4.934***
				(0.089)	(0.096)	(0.089)	(0.105)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	9,136	24,106	*Obs*	17,366	17,366	18,120	18,120
Pseudo R2	0.189	0.008	*R2*	0.002	0.227	0.014	0.195
mfx	0.223	0.861	*Adj R2*	0.001	0.227	0.014	0.195

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement		Post-participation Earnings	
I_SkillOS	0.505***	-0.032***		0.017	0.020	0.022	0.020
	(0.021)	(0.010)		(0.012)	(0.011)	(0.014)	(0.013)
log (Pre-Part Earnings)					-0.434***		0.330***
					(0.013)		(0.015)
Exit Yr UR 6-9%	-0.036	-0.016		0.023	-0.007	-0.022	0.008
	(0.027)	(0.011)		(0.016)	(0.013)	(0.016)	(0.016)
Exit Yr UR 9-12%	-0.064	-0.021		0.098***	-0.069**	-0.232***	-0.102***
	(0.055)	(0.019)		(0.024)	(0.021)	(0.028)	(0.026)
Exit Yr UR 12% higher	0.231	-0.029		0.080	-0.185***	-0.432***	-0.227***
	(0.225)	(0.039)		(0.045)	(0.041)	(0.050)	(0.050)
Constant				0.827***	4.647***	8.506***	5.601***
				(0.127)	(0.156)	(0.149)	(0.183)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	1,650	5,513	*Obs*	3,998	3,998	4,185	4,185
Pseudo R2	0.251	0.020	*R2*	0.013	0.268	0.044	0.163
mfx	0.258	0.861	*Adj R2*	0.01	0.266	0.042	0.161

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table A3. Skill Overshooting - Outcomes: High School Graduates & Equivalent

A. All observations

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_SkillOS	0.396***	-0.029***		0.023**	0.022***	0.026**	0.029***
	(0.011)	(0.005)		(0.007)	(0.006)	(0.008)	(0.008)
log (Pre-Part Earnings)					-0.401***		0.396***
					(0.007)		(0.009)
Constant				0.954***	4.415***	8.452***	5.037***
				(0.116)	(0.118)	(0.117)	(0.136)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	6,209	17,209	*Obs*	12,392	12,392	12,915	12,915
Pseudo R2	0.184	0.006	*R2*	0.003	0.244	0.013	0.187
mfx	0.226	0.860	*Adj R2*	0.002	0.243	0.013	0.187

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_SkillOS	0.508***	-0.023**		0.029*	0.020	0.017	0.025
	(0.027)	(0.011)		(0.015)	(0.013)	(0.017)	(0.016)
log (Pre-Part Earnings)					-0.426***		0.353***
					(0.016)		(0.018)
Exit Yr UR 6-9%	-0.067*	-0.025*		0.006	-0.023	-0.045*	-0.014
	(0.034)	(0.014)		(0.018)	(0.015)	(0.020)	(0.019)
Exit Yr UR 9-12%	-0.043	-0.051**		0.073**	-0.109***	-0.300***	-0.144***
	(0.069)	(0.026)		(0.028)	(0.026)	(0.033)	(0.031)
Exit Yr UR 12% higher		-0.062		0.034	-0.234***	-0.518***	-0.296***
		(0.048)		(0.055)	(0.051)	(0.062)	(0.061)
Constant				0.849***	4.611***	8.546***	5.430***
				(0.142)	(0.181)	(0.167)	(0.213)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	1,078	3,913	*Obs*	2,858	2,858	2,986	2,986
Pseudo R2	0.248	0.010	*R2*	0.011	0.247	0.055	0.181
mfx	0.277	0.859	*Adj R2*	0.007	0.244	0.052	0.178

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table A4. Wage Overshooting - Outcomes: All Education Levels

A. All observations

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.063***	-0.022***		0.076***	0.064***	0.037***	0.069***
	(0.007)	(0.006)		(0.006)	(0.006)	(0.008)	(0.007)
log (Pre-Part Earnings)					-0.249***		0.649***
					(0.011)		(0.012)
Constant				0.831***	3.034***	8.591***	2.842***
				(0.020)	(0.095)	(0.025)	(0.111)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	12,165	16,342	*Obs*	12,036	12,036	12,165	12,165
Pseudo R2	0.011	0.004	*R2*	0.013	0.06	0.006	0.207
mfx	0.144	0.860	*Adj R2*	0.013	0.059	0.005	0.206

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.058***	-0.023**		0.093***	0.078***	0.055***	0.085***
	(0.013)	(0.011)		(0.014)	(0.014)	(0.016)	(0.015)
log (Pre-Part Earnings)					-0.307***		0.576***
					(0.023)		(0.026)
Exit Yr UR 6-9%	-0.010	-0.020		-0.013	-0.024	-0.045*	-0.024
	(0.016)	(0.014)		(0.017)	(0.016)	(0.019)	(0.018)
Exit Yr UR 9-12%	-0.005	-0.019		-0.013	-0.093***	-0.259***	-0.110***
	(0.022)	(0.021)		(0.025)	(0.024)	(0.029)	(0.027)
Exit Yr UR 12% higher	-0.066*	-0.070		-0.041	-0.185***	-0.492***	-0.222***
	(0.038)	(0.052)		(0.049)	(0.048)	(0.058)	(0.055)
Constant				0.802***	3.565***	8.688***	3.508***
				(0.030)	(0.206)	(0.053)	(0.236)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	2,861	3,775	*Obs*	2,832	2,832	2,861	2,861
Pseudo R2	0.018	0.011	*R2*	0.024	0.085	0.053	0.198
mfx	0.127	0.869	*Adj R2*	0.02	0.082	0.049	0.195

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table A5. Wage Overshooting - Outcomes: High School Graduates & Equivalent

A. All observations

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.067***	-0.033***		0.072***	0.053***	0.027**	0.060***
	(0.009)	(0.007)		(0.009)	(0.009)	(0.010)	(0.010)
log (Pre-Part Earnings)					-0.331***		0.560***
					(0.014)		(0.017)
Constant				0.832***	3.769***	8.615***	3.646***
				(0.022)	(0.128)	(0.029)	(0.154)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	6,998	9,362	*Obs*	6,922	6,922	6,998	6,998
Pseudo R2	0.013	0.008	*R2*	0.012	0.083	0.005	0.146
mfx	0.141	0.865	*Adj_R2*	0.011	0.082	0.004	0.145

B. MSA sample only

	Upgrading	Reemployment		Wage Replacement Rate		Post-participation Earnings	
I_WageOS	0.048***	-0.029*		0.074***	0.056**	0.027	0.056**
	(0.017)	(0.015)		(0.018)	(0.017)	(0.021)	(0.020)
log (Pre-Part Earnings)					-0.347***		0.541***
					(0.027)		(0.032)
Exit Yr UR 6-9%	0.019	-0.031*		0.000	-0.015	-0.038	-0.013
	(0.019)	(0.018)		(0.021)	(0.019)	(0.023)	(0.021)
Exit Yr UR 9-12%	-0.002	-0.072**		0.009	-0.065*	-0.169***	-0.053
	(0.031)	(0.031)		(0.033)	(0.031)	(0.037)	(0.035)
Exit Yr UR 12% higher	-0.093**	-0.098		-0.124*	-0.283***	-0.567***	-0.317***
	(0.037)	(0.072)		(0.059)	(0.062)	(0.079)	(0.073)
Constant				0.782***	3.900***	8.674***	3.814***
				(0.041)	(0.247)	(0.062)	(0.292)
Exit Year	YES	YES		YES	YES	YES	YES
Obs	1,664	2,178	*Obs*	1,649	1,649	1,664	1,664
Pseudo R2	0.016	0.014	*R2*	0.016	0.093	0.033	0.165
mfx	0.125	0.878	*Adj R2*	0.01	0.087	0.027	0.16

***, **, and * denote coefficients significant at the 1%, 5%, and 10% levels, respectively.

Table A6. Skill Overshooting v. Skill Upgrading

Upgrading in years	Overshooting in years: -4 or less	-4 &-3	-3 &-2	-2 &-1	-1 &0	0 &1	1 &2	2 &3	3 &4	4 or more	Total %
less than -4	73.2	6.0	1.8	0.2	0	0.0	0	0	0	0	0.2
between -4 and -3	12.5	71.9	12.5	3.1	1.2	0.2	0	0	0	0	1.3
between -3 and -2	5.4	10.2	68.0	7.5	4.1	0.7	0.2	0.1	0	0	2.8
between -2 and -1	3.6	4.9	9.4	69.5	12.0	2.9	1.8	1.8	0.5	0	6.9
between -1 and 0	3.6	4.9	5.1	13.4	67.7	9.8	7.8	7.4	4.0	2.7	15.3
between 0 and 1	1.8	2.1	2.2	4.1	10.9	75.5	23.2	21.7	18.9	11.6	33.5
between 1 and 2	0	0	1.0	1.1	3.1	7.9	59.9	19.2	19.2	7.2	23.6
between 2 and 3	0	0	0	0.7	0.8	1.8	3.9	42.7	9.1	6.0	7.3
between 3 and 4	0	0	0	0.4	0.3	0.7	2.0	5.5	45.1	13.3	5.4
4 or more	0	0	0	0	0.1	0.5	0.9	1.6	3.2	59.2	3.6
Total Observations	56	285	721	1,620	3,748	8,553	8,843	3,279	2,285	1,422	30,812

i. This table is tabulated using only the participants who received occupational skills training, were reemployed, and have valid occupations codes for both training and reemployment (the balanced sample in Table 1).

ii. The figures show the share of each year of upgrading as a share of the category of overshooting listed on top. Each column sums up to 100%.

Table A7. Wage Overshooting v. Wage Upgrading

Wage upgrading	Wage Overshooting: Below 50%	50-75%	75-100%	100-125%	125-150%	over 150%	Total
Below 50%	61.2	30.8	16.2	11.1	7.1	5.0	19.1
50-75%	22.0	37.0	34.0	26.6	22.2	16.6	27.3
75-100%	11.3	20.2	28.5	30.4	27.8	22.4	24.3
100-125%	4.1	7.7	13.1	17.8	21.9	19.0	14.2
125-150%	0.9	2.7	4.7	7.9	10.9	13.0	6.9
over 150%	0.5	1.6	3.5	6.2	10.2	23.9	8.2
Total	4,747	9,814	11,200	8,590	5,610	10,286	50,247

[*] This table is tabulated using only the participants who received occupational skills training, were reemployed, and have valid occupations codes for both training and reemployment.