How do apprenticeships benefit young workers? An Evaluation of Registered Apprenticeship Programs in Ohio

2018-19 DOL Scholar Program

Tian Lou
The Ohio State University
lou.151@osu.edu

Joshua Hawley
The Ohio State University
Hawley.32@osu.edu

Abstract

In this project, we investigate how less-educated and less-experienced workers in Ohio benefit from registered apprenticeships. We focus on 18-24 years old males. Regression results show that compared to individuals who have similar pre-program educational backgrounds but have little or no job training, apprentices have significantly higher earnings six years after program entry. The wage premiums for apprentices persist for at least nine years after program entry. Additional analyses suggest that, among apprentices, apprenticeship completion is associated with 40 percent higher earnings. However, in Ohio, the enrollment of apprenticeship programs is low and around 50 percent of apprentices drop out of their programs. We conjecture that apprenticeship training benefits individuals because: 1) apprentices acquire work experience during their training; and 2) those who complete their programs get a nationally recognized certificate, which signals that they have high productivity to potential employers. Therefore, we also propose a discrete choice dynamic model, in which individuals make apprenticeship participation and completion decisions by considering how their decisions influence their future earnings. Note that since we only have access to Ohio data, results of this study are not nationally representative.

We acknowledge the support from the United States Department of Labor (DOL) Scholars Program. The views expressed are those of the authors and should not be attributed to DOL, nor does mention of trade names, commercial products, or organizations imply endorsement of same by the U.S. Government.

1. Introduction

The skill needs of the U.S. labor market have changed drastically since 1980. Due to ever-increasing automation, demand for routine workers, whose skills can be replaced by computers and machines, has decreased, and that for skilled workers has increased. Moreover, the wage inequality between skilled and unskilled workers has continually risen (Acemoglu and Autor, 2011). While college education is an effective way to accumulate human capital, its academically-oriented curriculum and high tuition costs may prevent some people from getting higher levels of education. Apprenticeships may be an alternative way to train workers with the skills firms need and help less-educated workers (i.e., high school dropouts or high school graduates) move up wage ladders. In an apprenticeship program, students spend most of their time in the workplace being trained by experienced journeymen. They also take related classes in local community colleges or high schools. In contrast to college students' debts, apprentices pay little for tuition and textbooks and are paid during their training.[1] However, they need to accept relatively low in-program wages in order to compensate firms for their training (Bilginsoy, 2003). Since firms typically provide apprenticeship programs based on their needs for skilled workers, this form of education intends to let apprentices acquire skills for in-demand jobs (Steedman, 2001).[2]

In recent years, the U.S. government has planned to expand apprenticeships. In 2017, President Trump signed an executive order, aiming to increase the number of apprentices in the U.S. to 5 million by 2022. Before that, the Obama administration spent $90 million to expand

[1] According to 2017 Digest of Education Statistics (Synder et al., 2019) Table 331.95, 61.8% of college seniors in 2015-16 received federal and/or nonfederal loans. The average cumulative loan amount for this cohort was $24,480 (2017 dollars).

[2] Many papers (for example, Becker (1962), Acemoglu and Pischke (1998), Lerman (2014)) have discussed firms' incentives for providing apprenticeships and what kinds of apprenticeship programs they provide. These topics are not in the scope of discussions for this paper. We take the availability of apprenticeship programs as given.

apprenticeships. However, currently, we have little empirical evidence regarding the effectiveness of U.S. apprenticeship programs. Many apprenticeship studies have focused on European countries, such as Germany (Krueger and Pischke, 1995; Winkelmann, 1996; Adda et al., 2013), Austria (Fersterer and Winter-Ember, 2003; Fersterer et al., 2008), Italy (Picchio and Staffolani 2017), and U.K. (McIntosh, 2005, 2007). These countries maintain fundamentally different apprenticeship systems and policies. For example, Germany has a dual apprenticeship system, that, in addition to work place training, requires at least one third of apprenticeship time be spent in the classroom (Parey, 2016). While U.S. apprenticeship programs also include classroom teaching, comparatively more emphasis is put on workplace training. Moreover, U.S. apprentices are on average older and enter their programs with some work experience (Eichhorst et al., 2015), while students in European countries can choose career and educational paths when they are in secondary school. Thus, apprenticeship studies of European countries may not be applicable to the U.S.

In the context of the increasing interest in apprenticeship programs, in this paper, we ask: do Ohio apprentices have higher earnings than individuals who have similar pre-program educational backgrounds but little or no job training? We specifically look at apprenticeship programs that are registered with the Ohio Apprenticeship Council.[3] Moreover, we are especially interested in less-educated workers who enter apprenticeship programs between the ages of 18-24, since they may benefit more from apprenticeship training than people with higher levels of education or more work experience.[4] Results based on this population may have implications regarding whether more resources should be allocated to encourage disadvantaged youths to

[3] Unregistered apprenticeship programs or the newly proposed industry recognized apprenticeship programs are not in the study scope of this paper.

[4] Throughout this paper, we define less-educated workers as those who do not have a college education, i.e., high school dropouts or high school graduates.

become apprentices. As Gregg and Tominey (2005) and Mroz and Savage (2006) suggested, youth unemployment has adverse impacts on future earnings, which may last until peoples' late 30s to early 40s. Apprenticeship training may partially offset their disadvantages in the labor market and provide stable employment and career paths with bright prospects.[5]

To investigate the effectiveness of apprenticeship programs in Ohio, we use data from the Registered Apprenticeship Partners Information Management Data System (RAPIDS), which contains detailed apprenticeship program information. Importantly, we are able to link the RAPIDS data with Ohio Unemployment Insurance (UI) Wage records and Higher Education Information (HEI) data to obtain each individual's pre- and post-training earnings and educational attainment. We use participants of Workforce Investment Act programs as the comparison group.

The results show that compared to individuals who have similar pre-program educational backgrounds but have little or no training, apprentices have 38% higher earnings six to nine years after program entry. The wage premiums are similar for cohorts who entered programs before, during, and after the financial crisis. Moreover, we also compare apprenticeship completers and dropouts and find that completers have 40 percent higher earnings than dropouts six to nine years after program entry. However, the wage differences between the completers and dropouts slightly reduce over time. Interestingly, the relative returns of completing apprenticeship programs are larger for cohorts who entered their programs before and during the recession.

Although our results show that apprenticeship completion is associated with more substantial payoffs than partial apprenticeship training, a significant percentage of apprentices in Ohio did

[5] For example, Büchel (2002) found that apprenticeship training in Germany improved the likelihood of getting high-quality jobs for workers with lower levels of general education. However, this trend disappeared as more low-ability apprentices entered the programs in recent years.

not complete their programs. Based on our data, around 50% of apprentices who entered their programs between 2006 and 2012 dropped out of their programs. Therefore, we also ask: if apprenticeships are beneficial, why would many apprentices leave before they finish? We conjecture that apprentices can get higher earnings for two reasons: 1) they accumulate work experience during their training; 2) the certificate apprentices get after completing their programs signals their productivity to the potential employers. Since apprentices' in-program wages are usually low, if partial apprenticeship training can help them find higher-paying jobs in the labor market, they may want to leave their programs before they acquire the certificates. Indeed, additional analysis indicates that apprenticeship dropouts and apprentices who were trained less than one year still have 14-17% higher earnings than people in the comparison group. Therefore, we also propose a discrete choice dynamic model, which can be used to further investigate the relative importance of apprenticeship training and certification in determining apprentices' wage growth rates. It can also be used to conduct counterfactual experiments to examine whether policies such as government subsidies to apprentices' in-program wages can increase apprenticeship participation and completion rates.

The paper proceeds as follows: in section 2, we discuss previous apprenticeship research; in section 3, we introduce the Ohio administrative data; section 4 includes the regression model and the discrete choice dynamic model; in the last section, we present the results.

2. Literature Review

Very few papers have examined the effectiveness of U.S. Registered Apprenticeships. Instead, many studies have focused on apprenticeship programs in European countries. Apprentices in those countries usually experience positive wage returns from their training. Analyses based on OLS regressions show that apprenticeship completers in Germany and Austria have 15-20%

higher earnings than non-apprentices. That represents a 5-7% increase in earnings per year of training given that apprenticeship programs in those countries usually last three years (Krueger and Pischke, 1995; Clark and Fahr, 2002; Fersterer and Winter-Ember, 2003; Riphahn and Zibrowius, 2016). Fersterer et al. (2008) looked at Austrian apprentices trained in small firms that shut down before their program completion. They instrumented these apprentices' training length with the time between when they entered the firm and the firm's closure. Their results indicate that one year of apprenticeship training increases workers' earnings by 2.5-4%, which is slightly smaller than previous research's findings. McIntosh (2005) found that in U.K., completing apprenticeships is associated with 5-7% higher incomes for male workers, but there are no wage returns for females. His later research (McIntosh, 2007) revealed that for more recent cohorts, the payoffs of apprenticeship training have risen and the wage returns for females who finished advanced apprenticeship training have become positive.

Although apprenticeship training can improve earnings, some researchers argued that the returns are not higher than that of college or vocational training (Clark and Fahr, 2002; Fersterer et al., 2008). However, apprenticeships have other potential benefits, such as smoothening people's school-to-work transitions and allowing them to get high-quality jobs. Winkelmann (1996) found that German apprentices had a shorter duration of unemployment between graduation and their first jobs than people with other types of formal education. Using more recent German data, Riphahn and Zibrowius (2016) observed that at age 25, apprentices are less likely to be unemployed or out of the labor force and are more likely to have permanent fulltime employment than non-apprentices. After correcting for the negative selections into apprenticeships, Bonnal et al. (2002) showed that French apprentices have higher probabilities of

getting jobs immediately after completing the training than vocational school students.[6] Corseuil et al. (2014) and Picchio and Staffolani (2017) respectively exploited a change in the maximum age for apprentices in Brazil and Italy. Their regression discontinuity analyses suggested that apprentices are more likely to find permanent jobs than people who enter the labor market as temporary workers.

While many U.S. firms also employ apprenticeships to train workers specific occupational skills, the U.S. apprenticeship model is somewhat different from that of other countries. Eichhorst et al. (2015) divided existing vocational systems into three categories: 1) vocational and technical secondary schools; 2) dual apprenticeship systems; and 3) formal apprenticeships. All three models include classroom teaching and workplace training, but the emphases of the three systems vary and the degrees of connection to the secondary education system are also different. Vocational and technical secondary schools mainly teach students in classrooms. The dual apprenticeship system stresses both workplace training and theoretical knowledge learning. The government and employers decide the training contents and bear the costs together. These two models are widely used by many European countries, while formal apprenticeships are more prevalent in the U.S.[7] Formal apprenticeships are usually firm-centered and have weaker links with the formal education system. Our focus in this paper are programs that are managed by the Registered Apprenticeship system.[8] Specifically, program sponsors, such as employers and/or unions, need to register with the U.S. Department of Labor Office of Apprenticeship (OA) or State Apprenticeship Agencies (SAA). For example, in Ohio, a program must be registered with

[6] However, Bonnal et al. (2002) also find that apprentices who cannot find jobs immediately after school may have a longer duration of unemployment.
[7] For example, according to Eichhorst et al. (2015), the vocational training programs in Spain, Italy, and France are mostly school-based. Germany, Austria, Denmark, and Switzerland adopt the dual apprenticeship system.
[8] There are unregistered apprenticeship programs as well. However, it is unclear how many apprentices are served by these programs (Lerman, 2012).

the Ohio Apprenticeship Council. The OA and SAAs ensure that these programs follow certain occupational standards, but program sponsors can decide the specific training contents (Lerman, 2012, 2018).

The institutional differences between European and U.S. apprenticeship systems lead to different apprentice compositions and working environment, which may impact the effectiveness of apprenticeship programs. For example, apprentices in many European countries start their training when they are still in or have just graduated from secondary schools (Fersterer et al., 2008; Parey, 2016), while U.S. apprentices may enter programs at later life stages, many of them already having work experience before starting their programs (Eichhorst et al., 2015).[9] How and whether their pre-program work experience is going to complement the skills acquired through apprenticeship training is unclear. Additionally, Adda et al. (2013) pointed out that the benefits of apprenticeship training may depend on the proportion of apprentices in the workforce. They simulated life-time wage profiles for German workers and found that apprentices have a moderate earning advantage over non-apprentices. They argued that on-the-job training leads to fast wage growth for non-apprentices in Germany, because they are exposed to a productive learning environment where the majority of workers are trained systematically through apprenticeships. However, in countries where apprenticeships are less prevalent, such as the U.S., the relative wage gains of apprentices may be larger.

Reed et al. (2012) examined the effectiveness of registered apprenticeship programs in ten states. They looked at apprentices who entered their programs in 2000. This allowed them to observe apprentices' short-term (six years after program entry) and medium-term (nine years after program entry) outcomes. They used a dosage model and found that apprenticeship

[9] Based on the Ohio registered apprenticeship data, the average age of 2006-2017 apprentices is 29, which is similar to the data in Lerman (2012) and Reed et al. (2012).

participants have much higher earnings and employment rates than non-participants in both the short term and medium term, but the payoffs slightly decrease in the medium term. Our research follows their definitions of short-term and medium-term outcomes. However, we examine how 18-24 years old high school dropouts or graduates may benefit from apprenticeship training. This group of people usually have difficulty getting or transitioning to high-quality jobs, which may further negatively impact their long-term earnings and employment. Moreover, we use multiple more recent cohorts to estimate apprentices' earning advantages over participants in labor market programs. Finally, we propose a dynamic discrete choice model to investigate the mechanisms through which apprenticeship participation may affect individuals' life-time earnings and employment status. We also discuss potential counterfactual experiments that we can conduct in future research.

3. Data

3.1. The Apprentices Sample

We utilize Ohio administrative data managed by the Ohio Longitudinal Data Archive for this research.[10] The main dataset used is from the Registered Apprenticeship Partners Information Management Data System (RAPIDS). It includes detailed program level and individual level information on apprentices. We focus on 18-24 years old males, who entered an apprenticeship program between 2006 and 2012. This allows us to observe at least one year of post-apprenticeship labor market outcomes.[11] [12] Our sample only includes male apprentices, because:

[10] The Ohio Longitudinal Data Archive (OLDA) is a project of the Ohio Education Research Center (oerc.osu.edu) and provides researchers with centralized access to administrative data. The OLDA is managed by The Ohio State University's CHRR (chrr.osu.edu) in collaboration with Ohio's state workforce and education agencies (ohioanalytics.gov), with those agencies providing oversight and funding. For information on OLDA sponsors, see http://chrr.osu.edu/projects/ohio-longitudinal-data-archive.

[11] The latest earning data we have is from 2018. Our data indicates that most of the apprenticeship programs in Ohio require 2,000 to 10,000 hours of training, which are equivalent to one to five years of training. Less than 3% of the programs require less than one year of training or more than five years of training. Table 1 shows that in our sample, the average required program length is 7,685 hours, which is about 4 years.

firstly, less than 5% of Ohio apprentices are female—the small sample size may lead to imprecise estimations; secondly, the female labor supply problem is more complicated to model, since the labor supply of females is more likely to be influenced by marriage and childcare than that of males (Keane et al., 2011).[13] [14] Moreover, around 10% of apprentices in the RAPIDS data are inmates. We do not include them in our sample, because unobserved juridical factors, such as what types of crime they committed and how long they stayed in prison, may have a more significant impact on their labor market outcomes than apprenticeship training.[15] Finally, we only look at individuals who are either high school dropouts or high school graduates, because they are more vulnerable in the labor market and may benefit more from apprenticeship training than people with higher levels of education or more work experience.[16]

Table 1 reports the descriptive statistics of the apprentice sample. The demographic compositions of Ohio apprentices show a lack of diversity. In our sample, about 87 percent are white, 93 percent are high school graduates, and 3.3 percent are veterans.[17] On average, Ohio apprentices spent 3.07 years in their programs. Some apprentices had previous training (technical instruction and on-the-job training) prior to starting their programs, which reduced their required

---

[12] We have 1979-2017 apprenticeship data. The sample sizes of the 1979-1992 cohorts are relatively small, varying between 1 to 1,147. We focus on the 2006-2012 sample because it consists of more recent larger cohorts. Also, our non-apprentice sample is drawn from WIA participant data, which is only available beginning in 2006.

[13] We have some family and fertility information for WIA participants, such as whether they are single parents or pregnant, but not for apprentices.

[14] In a typical dynamic model considering the female labor supply problem, researchers usually include factors such as marriage, fertility, childcare, and husbands' incomes (as did Eckstein and Wolpin (1989) and Eckstein and Lifshitz (2011)).

[15] For example, Western et al. (2001) and Western (2002) found that incarceration has negative effects on earnings and ex-inmates usually experience slow wage growth.

[16] This education group is also more likely to participate in apprenticeship programs than people with higher levels of education. Reed et al. (2012) assessed the effectiveness of apprenticeship programs in 10 states. Their descriptive statistics showed that around 90 percent of apprentices are high school dropouts and high school graduates. We also observe similar education compositions in our data. More than 97 percent of apprentices in Ohio are either high school dropouts or high school graduates.

[17] The descriptive statistics of all 2006-2012 non-inmate apprentices are in the Appendix Table A.1. The full sample has a slightly lower percentage of whites (81% vs. 87%) and a higher percentage of veterans (7.9% vs. 3.3%). The percentage of high school graduates is similar to that of the sample we use for our analysis.

program length. The average starting hourly wage for apprentices is $11.90, which is equivalent to earning $23,800 annually. As apprentices get more training, their in-program wages increase. The average exit hourly wage is $19.55, which is equivalent to a 17.5% annual increase in in-program wages. The proportion of apprentices in a union is about 66.7 percent.

We link the RAPIDS data with Ohio Unemployment Insurance (UI) Wage Records and Higher Education Information (HEI) data to track apprentices' and non-apprentices' educational and labor market outcomes at different life stages.[18] Specifically, in the Ohio UI Wage data, we have individuals' quarterly earnings matched to their industries, with records dating back to 1995. Thus, we are able to calculate individuals' pre-program and post-program earnings and work experience.[19] The UI Wage data comes from employers' payroll records. It is more accurate and reliable than self-reported data from surveys (Hotz and Scholz, 2002), which helps reduce measurement errors. Moreover, the UI Wage data covers the majority of employees in Ohio. Thus, we are able to calculate the average wage rates across different years and industries.[20] Finally, we take out people who had higher education based on HEI data, since these people's career choices and incomes are likely to be driven by their higher levels of education, rather than skills and experience acquired through apprenticeship programs.

---

[18] Linkages between these data sets are based on key IDs (pseudo IDs of individuals' social security numbers). Only around 58% of individuals in RAPIDS data had a valid key ID. The OLDA team recovered up to 92% of key IDs by using the probabilistic matching method.

[19] Work experience is measured by number of quarters being employed before a person entered his program. A person is defined as employed during a quarter if his income is greater than $100 during that quarter (Hollenbeck and Huang, 2016).

[20] However, Hotz and Scholz (2002) also mentioned two weakness of UI Wage Records: first, they don't include certain types of workers, such as self-employed, military, federal employees, and independent contractors. Therefore, if we don't observe a person in UI Wage Records during a certain period of time, we don't know whether he had any of the aforementioned jobs, was unemployed, moved out of Ohio or dropped out of the labor force. Second, since employers only report individual employee's earnings, we cannot get household level information from UI Wage Records.

Moreover, the limitation of the UI Wage data we have is that the earliest data is from 1995. This means we cannot accurately calculate older cohorts' pre-program outcomes.

After the linkages, we calculate apprentices' pre-program earnings and employment, and their earnings six to nine years after program entry.[21] An average apprentice had about three years of work experience before he started his apprenticeship program. The year before his program entry, he made $14,889. Six years later, he made $45,527, which is equivalent to a 20% annual increase in income. From six to nine years after program entry, his income increased by 3-5% each year.

We also show the descriptive statistics of apprenticeship completers and dropouts in Table 1. In general, apprentices who are white, high school graduates, in a union, and had more work experience and related training before program entry are more likely to finish their programs. Completers also have slightly higher earnings than dropouts before program entry (around $4,500 on average). However, six to nine years after program entry, a completer's average annual earnings are 1.7 times that of a dropout's (or $24,000 higher in annual income).[22] Moreover, completers had 2.18 years more training than dropouts on average, even though their required training lengths are similar.

3.2. The non-apprentice sample

The relative returns of apprenticeship programs partially depend on which comparison group is used. Previous research has compared apprentices with people who: enrolled in apprenticeship programs but never started them (Reed et al., 2012), people who entered the labor market without higher levels of education or formal training (Clark and Fahr, 2002; Adda et al., 2013), vocational school students (Parey, 2016; Riphahn and Zibrowius, 2016), and people with any other level of formal education (Krueger and Pischke, 1995; Winkelmann, 1996; Fersterer and Winter-Ember, 2003). In this paper, we provide evidence regarding the earning differences

[21] We can observe everyone's earnings six years after program entry. However, due to data and time restrictions, earnings seven to nine years after program entry of some cohorts are not available. For example, for those who started apprenticeship training in 2010, we can only observe their earnings six (2016), seven (2017), and eight (2018) years after program entry.

[22] We observe similar trends in the full sample in the Appendix Table A.1.

between apprentices and labor market program participants. Specifically, the non-apprentice sample is from 2006-2012 Workforce Investment Act Standardized Record Data (WIASRD). It includes information regarding participants in Workforce Investment Act (WIA) programs. Participants of WIA programs can get employment and training services based on their needs and progress made during their job searches (Decker and Berk, 2011).[23] Some of these training services may eventually lead to a diploma, certificate, or credential. However, many of these training programs did not last long and had low completion rates.[24] Thus, they may not have sufficiently improved participants' job skills. We dropped those who were in apprenticeship programs or had pursued higher education. Therefore, most of the WIA participants in our sample had limited or no job training.

Table 2 shows the descriptive statistics of the full sample and of the WIA participants. Similar to the apprentice sample, we look at individuals who are high school dropouts or high school graduates and were between ages 18-24 when they entered the program. Compared to apprentices, WIA participants are more diversified. More than 50 percent of WIA participants are non-white and more than 30 percent are high school dropouts.[25] Before entering the program, WIA participants have on average one year less work experience than apprentices. This may explain the pre-program earning differences between WIA participants and apprentices. Six to nine years later, people in both groups have higher earnings. However, the difference in the average earnings of the two groups increases from $9,214 to $25,285.

[23] According to Decker and Berk (2011), WIA services have three tiers: core service, intensive service, and training service. The first two tiers mainly provide job search assistance. If participants still cannot find jobs after getting core and intensive services, they may get into education or job training programs.

[24] Based on the research by Fortson et al. (2017), although the average WIA participant enrolls in more than one training program, he/she only spends 37-47 weeks or around 800 hours on these programs, which is far less than the length of most apprenticeship training.

[25] Before 2013, WIA data only recorded whether a participant is white and his/her ethnicity. Therefore, in this table, we divide race category as: white, Hispanic, and non-white non-Hispanic.

We also show the pre-program and post-program earning trends of WIA participants and apprentices in Figure 1. Before program entry, apprentices have slightly higher earnings than WIA participants, but their average earnings are below $20,000. The first year after starting their programs, apprentices have a big earning jump and their average income increase to more than $50,000 eight years after program entry. Interestingly, when we look at earning differences between different age groups (18-24 years old vs. 25-34 years old), the younger cohort of both apprentices and WIA participants have much lower earnings than the older cohort before program entry. However, the younger cohort of apprentices eventually catch up with their older cohorts' earnings, whereas WIA participants' earnings grew slowly and the earning difference between the younger cohort and the old cohort is significant and stays constant over time.

4. Model

4.1. Reduced-form Regression

We begin with a reduced-form model, which gives us the baseline results regarding the associations between apprenticeship training and earnings. Equation (1) shows the earning regression,

$$Ln(Y)_{ijckt} = \gamma_0 + \gamma_1 A_i + X_{it}\gamma_x + \tau_t + \pi_j + \rho_c + \omega_k + \xi_{ijckt} \qquad (1)$$

where Y_{ijckt} is individual i's earnings during the sixth to ninth year after program entry.[26] By that time, most of the apprentices and WIA participants should have left their programs. The labor market area where individual i is living, his cohort, and the industry he is working in are

[26] According to Reed et al. (2012), they defined outcomes six years after program entry as short-term outcomes and nine years after program entry as middle-term outcomes. We use the same definition to be consistent with Reed et al. (2012).

indexed as j, c, and k, respectively. Ohio's labor market areas are shown in Figure 2.[27] A person's cohort is defined by the year he entered his program.

Apprenticeship participation is represented by A_i, which is equal to one for apprentices and zero for non-apprentices. The coefficient, γ_1, represents the relationship between apprenticeship training and post-program earnings. The regression also controls for individual characteristics, X_i, including age, age squared, race, education level, and earnings and work experience before program entry. These control variables account for earning differences among people with different observed characteristics. The pre-program labor market outcomes partially capture individual i's work ability. Random error is represented by ξ_{ijckt}.

We also include year fixed effects, τ_t, labor market fixed effects, π_j, cohort fixed effects, ρ_c, and industry fixed effects, ω_k. These fixed effects reduce the bias caused by observed and unobserved local labor market conditions and earning differences for different cohorts and different industries. For example, during the financial crisis, the unemployment rate for high school dropouts and high school graduates increased significantly, which may had led to higher apprenticeship and/or WIA program participation. This implies that, everything else being equal, a person in the 2008 cohort may have higher unobserved ability than a person in the 2012 cohort, because his program participation may be mainly driven by the economic conditions rather than his employability. Moreover, since we use multiple years of observations, we include year fixed effects to control for earning differences across years. Additionally, apprentices are more likely

[27] Ohio's Department of Jobs and Family Services (n.d.) divides counties in Ohio into nine labor market areas based on metropolitan statistical areas, combined statistical areas, and workforce commuting patterns. Within a labor market area, individuals can easily find or change jobs without changing their residential locations. We argue that it is more reasonable to use the labor market area a person is living in than the county he is living in for analysis, because it is common for some people to commute between counties. These people's earnings are influenced by their working counties' labor market conditions, rather than their living counties' conditions. Since the UI Wage data does not provide working locations, we use their locations shown in the Bureau of Motor Vehicle (BMV) data as an estimate of their labor market areas.

to have jobs in the construction and manufacturing industry, whereas WIA participants are more likely to work in the administrative and support services and food services industries. Therefore, we use industry fixed effects to capture the earning differences across industries.[28] However, we recognize that even after controlling for pre-program outcomes and these fixed effects, the coefficient of the apprentice indicator only represents the correlation between apprenticeship training and future earnings. We cannot rule out the possibility that individuals choose different programs based on factors that are unobserved by researchers, such as ability, motivation, cognitive skills, and family backgrounds. For example, compared to WIA participants, apprentices may have better labor market outcomes not only because they received apprenticeship training but also because they have greater innate ability or are more motivated. Therefore, even without any training, they may still have performed better than WIA participants.

4.2. The Discrete Choice Dynamic Model

In addition to the reduced-form models, labor economists also use dynamic models to answer questions related to labor supply (Eckstein and Wolpin, 1989; Blundell et al., 2016), wage determinations (Wolpin, 1992; Altonji et al. 2013), and occupation and education decisions (Keane and Wolpin, 1997; Eckstein and Wolpin, 1999; Arcidiacono, 2005). The advantage of the dynamic model is that it allows researchers to: 1) explicitly model individuals' decision-making rules; 2) conduct counterfactual experiments to see how policy changes affect individuals' decisions (Wolpin, 2013). The only apprenticeship paper that used the dynamic model is Adda et al. (2013). They modeled apprenticeship participation decisions and life-time labor supply and

[28] A comment we received during the presentation at the Department of Labor is that one of the mechanisms that apprenticeship training increases earnings is through industries. Adding industry fixed effects may understate the earning advantages of apprentices. Therefore, in the results section, we also show estimations without industry fixed effects.

wage growth of Germans who chose to follow the vocational track at age 10.[29] However, as discussed in the literature review section, the German apprenticeship system, compositions of apprentices, and working environment are different from the U.S. ones. Therefore, the specific model setups and individual decision-making rules proposed in this paper are different from Adda et al. (2013)'s model. For example, non-apprentices in our model may become apprentices at any time between ages 18-24, whereas in Adda et al.'s model, individuals only make apprenticeship participation decision once—when they were 16 years old. Moreover, Adda et al. (2013) did not incorporate completion decisions and counted apprentices who started but did not finish their training as non-apprentices, while our model also include whether and to what extent partially trained apprentices experience wage growth in the labor market.[30]

In this section, we describe the discrete choice dynamic model in which people decide their apprenticeship participation and/or labor supply at each time period based on wages and costs associated with each potential choice and their expectations of future utilities. The model starts at age 18. [31] Individual's initial education status, either having a high school degree or no degree, have been decided by themselves and/or their parents. Education status is used to measure individuals' potential abilities. It is unlikely to change significantly, since we dropped those who had education beyond high school.[32]

[29] Students in Germany can choose two paths when they are 10, an academic track or a vocational track. The academic track usually leads to university learning, while the vocational track leads to vocational schools, apprenticeships, or work without further training.

[30] This setup applies to Germany, because most German apprentices finish their training. Those who quit before finishing are more likely to be unqualified apprentices. They are more similar to workers without any training.

[31] The minimum required age for most apprenticeship programs is 16. We could begin the model with age 16. However, the percent of apprentices who started their programs at ages 16 and 17 is very small (around 0.2%).

[32] We matched our sample to HEI data and dropped those who had an associate or a higher level of degree. These people are around 5% of the full sample.

Following Adda et al. (2013), we use quarter as the unit of time.[33] Before becoming an apprentice, each quarter, individuals choose from three labor market statuses: 1) entering or staying in an apprenticeship program (A); 2) working in the labor market (E); 3) being unemployed (U). We refer labor market jobs specifically to jobs that are not in apprenticeship programs. Thus, the choice set for individual i at time t is denoted by d_{it}^{l}, where $l \in \{A, E, U\}$. The choice variable d_{it}^{l} equals to 1 if individual i chooses labor market status l, and 0 otherwise. Once a person enters an apprenticeship program, in the following quarters, he decides whether to continue the apprenticeship training or leave the program until he finishes. Once quit or finish the program, his choice set only contains two options, working (E) or not working (U).[34] [35]

Individual i's utility associated with working (in an apprenticeship program or in the labor market) is a linear function of net wage, W_{it}^{l}, and costs associated with the choice, c_{it}^{l}.[36] Specifically, net wage at time t is shown in Equation (3). It is a fraction of individual i's market wage, which is determined by cumulative work experience as an apprentice (e_{it}^{A}), cumulative work experience in the labor market (e_{it}^{E}), an indicator of whether the person has completed his program (A_{it}), individual i's own characteristics (X_{it}), and a transitory shock to wages (ϵ_{it}^{l}). The fraction of the market wage a person can get is represented by the parameter λ_{it}^{l}, which has two cases. First, if individual i is in an apprenticeship program during time t, λ_{it}^{A} is a positive number between zero and one, depending on the specific program and how long he has stayed in the program. This is because an apprentice needs to compensate his training firm by accepting wages

[33] This is not only consistent with the previous model, but also consistent with the data structure. The UI Wage data report a person's total earning each quarter.

[34] We use the same notation for working in the labor market as a non-apprentice as we do for an apprentice working after completing his program, because they are essentially both labor supply choice.

[35] To simplify the model, we assume that once an apprentice left his program, he would not reenter the same program or start a new program. According to our data, less than 3% of apprentices entered more than one program and less than 0.4% of apprentices restarted their programs after leaving. Therefore, our assumption should not lead to significant estimation bias.

[36] We assume that individuals do not save.

that are lower than his true marginal productivity (which is equal to his market wage). Second, if individual i is working in the labor market during time t, λ_{it}^{E} is equal to one.

$$U_{it}^{l} = W_{it}^{l} - c_{it}^{l} \qquad (2)$$

$$W_{it}^{l} = \lambda_{it}^{l} W\left(X_{it}, e_{it}^{A}, e_{it}^{E}, A_{it}, \epsilon_{it}^{l}\right) \qquad (3)$$

In addition to wages, individuals also face different costs when in different statuses. Equation (4) is the cost function associated with labor market choice l. It has two terms. First, a transition from apprenticeship to an official job (unskilled or skilled) may engender job search costs, $s_{it}(e_{it}^{A}, e_{i}^{E}{}_{t})$, which may vary with a person's work experience. For example, an apprentice who stayed in his program longer may build a larger job network than someone who stayed in the program for a short period of time. Moreover, an apprentice who have more labor market work experience may also be easier to find a job than those who never had labor market jobs. Second, following Cunha et al. (2005), the cost function also includes psychic costs, φ_{it}.[37] This may be especially true for someone who entered an apprenticeship program after working in the labor market for a few years, because apprenticeship programs involve some classroom learning and may pay lower wages than their current jobs. The indicator function, $I\left(d_{i}^{A}{}_{,t-1} = 0\right)$ is equal to one if a person was not in an apprenticeship during time period $t - 1$.

$$c_{it}^{l} = C\left(s_{it}(e_{it}^{A}),\ \varphi_{it} I\left(d_{i,t-1}^{A} = 0\right) d_{it}^{A}\right)$$

Given the wage and cost functions, we write the utility functions of being an apprentice and working in the labor market in Equations (5) and (6). If a person chooses not to work during time period t, his utility is determined by the net benefit of home production, $\bar{U}_{U}$, which is constant,

[37] In Cunha et al. (2005), they found that tuition costs alone cannot explain why individuals who could have large returns from college did not go to college. They pointed out that the psychic cost is an important factor to consider when calculate the net return of education.

and a transitory shock, ϵ^U . We assume the transitory shocks in the three utility functions follow a joint normal distribution and are not serially correlated.

$$U_{it}^{\boldsymbol{A}} = \lambda_{it}^{A} W\left(X_{it}, e_{it}^{\boldsymbol{A}}, e_{it}^{E}, A_{it}, \epsilon_{it}^{A}\right) - C\left(s_{it}\left(e_{it}^{\boldsymbol{A}}, e_{it}^{E}\right),\ \varphi_{it} I\left(d_{i,t-1}^{A} = 0\right)\right) \quad (5)$$

$$U_{it}^{E} = W\left(X_{it}, e_{it}^{\boldsymbol{A}}, e_{it}^{E}, A_{it}, \epsilon_{it}^{E}\right) - C\left(s_{it}\left(e_{it}^{\boldsymbol{A}}, e_{it}^{E}\right)\right) \quad (6)$$

$$U_{it}^{\boldsymbol{U}} = \bar{U}_U + \epsilon_{it}^{\boldsymbol{U}} \quad (7)$$

At time t , the expected present discounted 1value for choice l is given by Equation (8), where Ω_{it} is the state space, $\Omega_{it} = \{X_{it},\ e_{it}^{A}, e_{it}^{E}, A_{it}, \epsilon_{it}^{A}, \epsilon_{it}^{E}, \epsilon_{it}^{U}\}$. Individual i makes a labor market choice to maximize the sum of his current utility and his future discounted utility.

$$V_{i\,t}^{\,l}(\Omega_{it}) = U_{i\,t}^{\,l}(\Omega_{it}) + \delta E\left[V_{t+1}\left(\Omega_{i,t+1}\right)\middle|\Omega_{it}, D_{it} = k\right] \quad \forall\, t < T \quad (8)$$

$$= U_{iT}^{l}(\Omega_{iT}) \qquad \forall\, t = T$$

$$V_{it}(\Omega_{it}) = \max_{d_{it}^{l}}(V_t^{A}(\Omega_{it}), V_t^{E}(\Omega_{it}), V_t^{U}(\Omega_{it})) \quad (9)$$

5. Results

5.1 Apprentices vs. WIA participants

The estimated results of Equation (1) are presented in Table 3. The first three Columns show how much the fixed effects can explain the correlation between apprenticeship training and earnings six to nine years after program entry. When comparing Column 2 with Column 1, adding year fixed effects, labor market fixed effects and cohort fixed effects slightly increases the coefficient of the apprentice indicator. However, after controlling for industry fixed effects, the coefficient decreases by about 50 percent. This implies that apprenticeship training may greatly improve individuals' future earnings by helping them get jobs in more profitable industries.

In Columns 4 and 6 of Table 3, we gradually add demographic variables and pre-program labor market outcomes into the regressions. Although these variables decrease the coefficient of the apprentice indicator, it stays positive and statistically significant at 1 percent level. The result in Column 6 indicates that the log earnings of apprentices are 0.326 higher than those of WIA participants. In other words, holding everything else constant, an apprentice's income is 38.5 percent higher than that of a similar WIA participant. If we do not remove the earning differences across industries, the coefficient in Column 5 is twice the coefficient in Column 6, which implies 91% higher earnings for apprentices. [38]

We also test whether apprentices' earning advantages change over time. Table 4 shows the relationship between apprenticeship training and earnings for each post-program year separately. Because the most recent UI Wage data available is from 2018, we use different cohorts when testing longer term results. Based on Columns 1-4 of Table 4, despite small fluctuations, the wage premiums of apprentices persist nine years after program entry. This result is similar to Reed et al. (2012). However, they find that the medium term returns to apprenticeship training are slightly smaller than the short-term returns.

In Table 5, we show results for several subgroups. First, the benefits of apprenticeship participation for non-white apprentices are only half of that for white apprentices. This is probably because non-white apprentices are more likely to drop out of their programs. Panel A of Table 8 suggests that after completing training, non-white apprentices actually have higher earning returns than white apprentices. Second, Bilginsoy (2007) and Berick et al. (2011) point

[38] In Appendix Table A.2. Panels B and C, we show our results for older cohorts. The wage premiums of older apprentices are smaller than those of younger cohorts. Their wage premiums are only half of the youngest cohort's wage premiums, regardless whether we add the industry fixed effects. We are also concerned that because more than 90 percent of apprentices are high school graduates (compared with 70 percent of WIA participants), they may have higher unobserved ability than WIA participants. In Panel D of Table A.2., we show the results of regressions only using high school graduates. The results are very similar to the results of the full sample. Although we cannot entirely rule out the possibility that people with higher unobserved ability are selecting into apprenticeship programs, the small change in results indicates that the degree of selection should be small.

out that apprenticeship dropouts usually leave before they gain substantial skills and may not be able to get high-skilled jobs. In Panel C, we compare WIA participants with apprenticeship dropouts and find that partial apprenticeship training is still associated with higher earnings. However, the earning difference is much lower than the outcome in the full sample. Third, some WIA participants have received short-term trainings. We test whether their returns are comparable to the returns of short apprenticeship training. Panel D shows that, when we include industry fixed effects, apprentices who stayed in their programs less than one year have about 16% higher earnings than WIA participants. Finally, the returns for apprentices vary by their required training lengths. Apprentices in programs that require less than three years training experience lower returns than those in programs that require longer training.

5.2 Apprenticeship Completers vs. Dropouts

In the previous section, we found that apprentices have significantly higher earnings than people who have similar pre-program educational backgrounds but have little or no job training. This is true even when we only consider apprentices who were trained briefly or who were in programs that require shorter training lengths. However, among apprenticeship participants, only completers can obtain nationally recognized certificates which differentiate them from other less-educated workers and may substantially increase their future earnings. In our sample, around 48% of apprentices never completed their programs.[39] Thus, in this section, we examine the wage premiums for apprenticeship completers.

In Table 6, we use a model similar to Equation (1). Since RAPIDS data recorded the occupation an apprentice was trained in, we also add occupation fixed effects to account for earning differences due to different training content. When comparing results from Columns 2

[39] In the full sample, the dropout rate is slightly higher (51%). This is because our sample only includes those who have positive earnings six to nine years after program entry. See Appendix Table A.5. for details.

and 3, the occupation fixed effects reduce the coefficient of the program completer indicator by about 15%. After controlling for demographic variables and a variety of apprenticeship program variables, we find that the log earnings of apprenticeship completers are 0.337 higher than those of dropouts six to nine years after program entry, which implies, that everything else being equal, completers have 40% higher earnings than dropouts.[40] Results of each years' earnings are presented in Table 7. As when we compared apprentices and WIA participants, we again find the rewards for completing apprenticeship programs are relatively stable over time. Except for the 2006-2009 cohorts, wage premiums for completers nine years after program entry reduced by 20% when compared with earnings six years after program entry.

In addition, our sample includes people who joined their programs during or immediately after the 2008 financial crisis. We conjecture that, on average, they may have higher ability than workers in the other cohorts, because even high-ability workers may find it hard to get jobs during a recession. Apprenticeships offer them a way to gain human capital and get temporary jobs. Similarly, high-ability workers may also be more likely to seek help through WIA programs during economic downturns than during economic booms. In the last three columns of Table 4 and Table 7, we split our samples into three cohort groups and show their outcomes six years after program entry.[41] The results indicate that returns on apprenticeship participation for the recession cohort (2008-10) are very similar to the returns for the other two cohorts. This implies that the degree of high-ability workers sorting into apprenticeship programs may be similar to that of WIA programs.

[40] Returns on apprenticeship completion for different age groups are shown in Appendix Table A.3. Interestingly, unlike the findings in Table A.2. (lower returns for older cohorts when comparing all apprentices with WIA participants), older apprenticeship completers enjoy slightly higher returns than the younger cohorts.

[41] According to the U.S. National Bureau of Economic Research, the last financial crisis began in December 2007 and ended in June 2009. We also include the 2010 cohort because although the economy began to recover at that time, less-educated people's unemployment rate stayed high. During this time, the unemployment rate of high school dropouts and high school graduates remained above 11% and 8%, respectively (Bureau of Labor Statistics, 2018). In our data, we observe that the number of apprentices consistently decreased during these three years.

However, when we look at the relative returns between apprenticeship completers and dropouts, we find that the 2008-10 cohorts have lower returns than the pre-recession cohorts but have higher returns than the post-recession cohorts.[42] Previous research (Bilginsoy, 2003) shows that the time apprentices stayed in their program changes procyclical with the business cycle. Our results may further suggest that the ability level of apprenticeship dropouts also varies with the business cycle. When the economy slows down, the availability of apprenticeships may decrease, because many apprenticeship programs are in industries that were hit hard by the recession, such as construction and manufacturing.[43] Therefore, low-ability workers may have to leave first when the training firms curtail their programs. This trend widens the earning differences between completers and dropouts. However, when the economy recovers, high-ability workers are able to find decent jobs in the labor market and thus may be more likely to leave their programs before completion.

Table 8 presents results of heterogeneity tests. Earlier research suggests that the quality of apprenticeship programs may vary with whether the program is sponsored jointly by employers and unions or unilaterally sponsored by employers (Berik and Bilginsoy, 2000; Bilginsoy, 2003) and the size of the training firm (Soskice, 1994; Winkelmann, 1996). We find that apprenticeship completers benefit more from training in programs that are jointly sponsored and managed by unions. Moreover, apprenticeship completers in medium-sized and large-sized firms all experience high earning returns, while the earning difference between completers and dropouts in small-sized firms are much smaller.

[42] Estimations by using all 2006-2012 non-inmate apprentices are shown in Appendix Table A.4. The findings are similar.

[43] Early research (Merrilees, 1983) argues that recessions should have moderate impacts on the availability of apprenticeships, because firms could spend this time on training workers. When the economy recovers, firms will have more skilled laborers to increase their production. However, Askilden and Nilsen (2005) claim that instead of an investment, apprentices are substitutes for skilled workers. They show that the recruitment of apprentices is cyclical. The pattern in our data is consistent with Askilden and Nilsen (2005): i.e., the number of new apprentices dropped significantly between 2008 and 2010.

Conclusion

As many jobs in the U.S. labor market require education and training beyond high school, it is especially difficult for less-educated youths to find jobs and step into promising career paths. Many of them seek help through employment and job training programs. In this paper, we show that apprenticeships may provide disadvantaged youths with a more effective way to accumulate work skills and realize substantial wage gains. Specifically, using Ohio administrative data, we find that among 18-24 years old high school dropouts or high school graduates, apprentices have significantly higher earnings than WIA program participants six to nine years after program entry. However, although apprenticeship training is associated with positive payoffs, around 50% of Ohio apprentices dropped out before completing their programs. Additional analyses suggest that while partially trained apprentices still earn higher incomes than WIA participants, the earning difference between apprenticeship completers and dropouts is large and persists over time. These results imply that although partial apprenticeship training is beneficial, it is not enough to lead to high-quality jobs.

From a policy perspective, instead of short-term training and temporary work placement, encouraging qualified job training program participants to become apprentices may help them gain more useful jobs skills and provide firms with more skilled workers. This may also reduce job training programs' cost burdens, since firms usually pay for apprentices' training. In addition to job training programs, high schools and community colleges can build more connections with apprenticeship providers so that it is easier for young people who are less interested in academics to learn about and enroll in apprenticeship programs. Another important policy issue is how to improve apprenticeship completion rates. Apprenticeship dropouts not only do not build substantial skills, but they also waste firms' resources, which may discourage firms from

providing more apprenticeships. To explore potential policy interventions, we also propose a discrete choice dynamic model in which individuals make apprenticeship participation and completion decisions while taking into account their potential future earnings. In the future research, we will estimate this model to investigate the potential mechanisms through which apprenticeships improve individuals' earnings, and we will conduct counterfactual experiments to see how policy interventions, such as subsidies to apprentices' in-program wages would increase apprenticeship participation and completion rates.

This paper has several limitations. First, our results only represent returns for apprenticeship training for males. Whether and how much females can benefit from apprenticeship programs is unclear. Second, many programs in our samples are in the manufacturing and construction industries. Our findings may not apply as well to certain newly developed programs, such as those in healthcare, IT, retail, and finance. Programs in these industries may have different skill requirements and lead to different wage gains. Third, this paper only considers the payoffs for apprentices. Whether training firms can reap benefits may affect the availability and quality of apprenticeships. Finally, we may overstate the returns to apprenticeship training, given that our comparison group consists of people who needed help in looking for jobs. Future research can look at the relative returns of apprenticeships to other forms of education.

Reference

Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043-1171). Elsevier.

Acemoglu, D., & Pischke, J. S. (1998). Why do firms train? Theory and evidence. *The Quarterly Journal of Economics*, *113*(1), 79-119.

Adda, J., Dustmann, C., Meghir, C., & Robin, J. M. (2013). *Career progression, economic downturns, and skills* (No. w18832). National Bureau of Economic Research.

Altonji, J. G., Smith Jr, A. A., & Vidangos, I. (2013). Modeling earnings dynamics. *Econometrica*, *81*(4), 1395-1454.

Arcidiacono, P. (2005). Affirmative action in higher education: How do admission and financial aid rules affect future earnings?. *Econometrica*, *73*(5), 1477-1524.

Askilden, J. E., & Nilsen, Ø. A. (2005). Apprentices and young workers: A study of the Norwegian youth labour market. *Scottish Journal of Political Economy*, *52*(1), 1-17.

Becker, G. S. (1962). Investment in human capital: A theoretical analysis. *Journal of political economy*, *70*(5, Part 2), 9-49.

Berik, G., & Bilginsoy, C. (2000). Do unions help or hinder women in training? Apprenticeship programs in the United States. *Industrial Relations: A Journal of Economy and Society*, *39*(4), 600-624.

Berik, G., Bilginsoy, C., & Williams, L. S. (2011). Gender and racial training gaps in Oregon apprenticeship programs. *Labor Studies Journal*, *36*(2), 221-244.

Bilginsoy, C. (2003). The hazards of training: Attrition and retention in construction industry apprenticeship programs. *ILR Review*, *57*(1), 54-67.

Bilginsoy, C. (2007). Delivering skills: Apprenticeship program sponsorship and transition from training. *Industrial Relations: A Journal of Economy and Society*, *46*(4), 738-765.

Blundell, R., Costa Dias, M., Meghir, C., & Shaw, J. (2016). Female labor supply, human capital, and welfare reform. *Econometrica*, *84*(5), 1705-1753.

Bonnal, L., Mendes, S., & Sofer, C. (2002). School-to-work transition: apprenticeship versus vocational school in France. *International journal of manpower*, *23*(5), 426-442.

Büchel, F. (2002). Successful apprenticeship-to-work transitions: On the long-term change in significance of the German school-leaving certificate. *International Journal of Manpower*, *23*(5), 394-410.

Clark, D., & Fahr, R. (2002). The promise of workplace training for non-college-bound youth: theory and evidence from German apprenticeship.

Corseuil, C. H., Foguel, M., Gonzaga, G., & Ribeiro, E. P. (2014). *Youth Turnover in Brazil: Job and Worker Flows and an Evaluation of a Youth-Targeted Training Program* (No. 155). Documento de Trabajo.

Cunha, F., Heckman, J., & Navarro, S. (2005). Separating uncertainty from heterogeneity in life cycle earnings. *oxford Economic papers*, *57*(2), 191-261.

Decker, P. T., & Berk, J. A. (2011). Ten years of the Workforce Investment Act (WIA): Interpreting the research on WIA and related programs. *Journal of Policy Analysis and Management*, *30*(4), 906-926.

Eckstein, Z., & Lifshitz, O. (2011). Dynamic female labor supply. *Econometrica*, *79*(6), 1675-1726.

Eckstein, Z., & Wolpin, K. I. (1989). Dynamic labour force participation of married women and endogenous work experience. *The Review of Economic Studies*, *56*(3), 375-390.

Eckstein, Z., & Wolpin, K. I. (1999). Why youths drop out of high school: The impact of preferences, opportunities, and abilities. *Econometrica*, *67*(6), 1295-1339.

Eichhorst, W., Rodriguez-Planas, N., Schmidl, R., & Zimmermann, K. F. (2015). A road map to vocational education and training in industrialized countries. *ILR Review*, *68*(2), 314-337.

Fersterer, J., & Winter-Ebmer, R. (2003). Are Austrian returns to education falling over time?. *Labour economics*, *10*(1), 73-89.

Fersterer, J., Pischke, J. S., & Winter-Ebmer, R. (2008). Returns to apprenticeship training in Austria: Evidence from failed firms. *Scandinavian journal of economics*, *110*(4), 733-753.

Fortson, K., Rotz, D., Burkander, P., Mastri, A., Schochet, P., Rosenberg, L., ... & D'Amico, R. (2017). Providing Public Workforce Services to Job Seekers: 30-Month Impact Findings on the WIA Adult and Dislocated Worker Programs. *Mathematica Policy Research and Social Policy Research Associates*.

Gregg, P., & Tominey, E. (2005). The wage scar from male youth unemployment. *Labour Economics*, *12*(4), 487-509.

Hotz, V. J., & Scholz, J. K. (2002). Measuring employment and income for low-income populations with administrative and survey data. *Studies of welfare populations: Data collection and research issues*, 275-315.

Keane, M. P., & Wolpin, K. I. (1997). The career decisions of young men. *Journal of political Economy*, *105*(3), 473-522.

Krueger, A. B., & Pischke, J. S. (1995). A comparative analysis of East and West German labor markets: before and after unification. In *Differences and changes in wage structures* (pp. 405-446). University of Chicago Press.

Lerman, R. I. (2012). *Can the United States expand apprenticeship? Lessons from experience* (No. 46). IZA Policy Paper.

Lerman, R. (2014). Do firms benefit from apprenticeship investments?. *IZA World of Labor*.

Lerman, R. I. (2018) Building a Robust Apprenticeship System in the U.S.: Why and How. Presentation at the 2018 ASSA Annual Meeting. https://www.aeaweb.org/conference/2018/preliminary/paper/GE3a733s

McIntosh, S. (2005). The returns to apprenticeship training. *Journal of Education and Work*, *18*(3), 251-282.

McIntosh, S. (2007). *A cost-benefit analysis of apprenticeships and other vocational qualifications*. Nottingham: Department for Education and Skills.

Merrilees 1, W. J. (1983). Alternative models of apprentice recruitment: with special reference to the British engineering industry. *Applied Economics*, *15*(1), 1-21.

Mroz, T. A., & Savage, T. H. (2006). The long-term effects of youth unemployment. *Journal of Human Resources*, *41*(2), 259-293.

Parey, M. (2016). Vocational Schooling versus Apprenticeship Training. Evidence from Vacancy Data.

Picchio, M., & Staffolani, S. (2017). Does apprenticeship improve job opportunities? A regression discontinuity approach. *Empirical Economics*, 1-38.

Reed, D., Liu, A. Y. H., Kleinman, R., Mastri, A., Reed, D., Sattar, S., & Ziegler, J. (2012). *An effectiveness assessment and cost-benefit analysis of registered apprenticeship in 10 states* (No. 1b5795d01e8a42239b3c98dcc1e1161a). Mathematica Policy Research.

Riphahn, R. T., & Zibrowius, M. (2016). Apprenticeship, vocational training, and early labor market outcomes–evidence from East and West Germany. *Education Economics*, *24*(1), 33-57.

Snyder, T. D., De Brey, C., & Dillow, S. A. (2019). Digest of Education Statistics 2017, NCES 2018-070. *National Center for Education Statistics*.

Soskice, D. (1994). Reconciling markets and institutions: The German apprenticeship system. In *Training and the private sector: International comparisons* (pp. 25-60). University of Chicago Press.

Steedman, H. (2001). *Benchmarking apprenticeship: UK and continental Europe compared*. Centre for Economic Performance, London School of Economics and Political Science.

Western, B., Kling, J. R., & Weiman, D. F. (2001). The labor market consequences of incarceration. *Crime & delinquency*, *47*(3), 410-427.

Western, B. (2002). The impact of incarceration on wage mobility and inequality. *American sociological review*, 526-546.

Winkelmann, R. (1996). Employment prospects and skill acquisition of apprenticeship-trained workers in Germany. *ILR Review*, *49*(4), 658-672.

Wolpin, K. I. (1992). The determinants of black-white differences in early employment careers: Search, layoffs, quits, and endogenous wage growth. *Journal of Political Economy*, *100*(3), 535-560.

Wolpin, K. I. (2013). *The limits of inference without theory*. MIT Press.

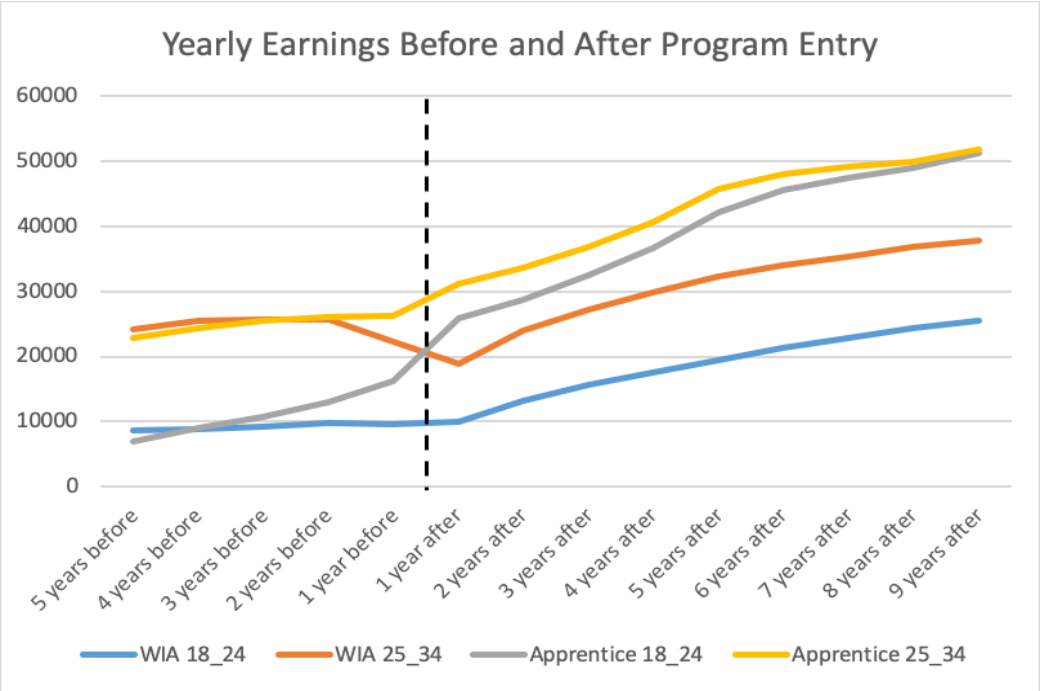

Figure 1. Yearly Earnings of Apprentices and WIA Participants Before and After Program Entry

Notes: All earnings are adjusted to 2018 price level. The black dash line represents the program entry.

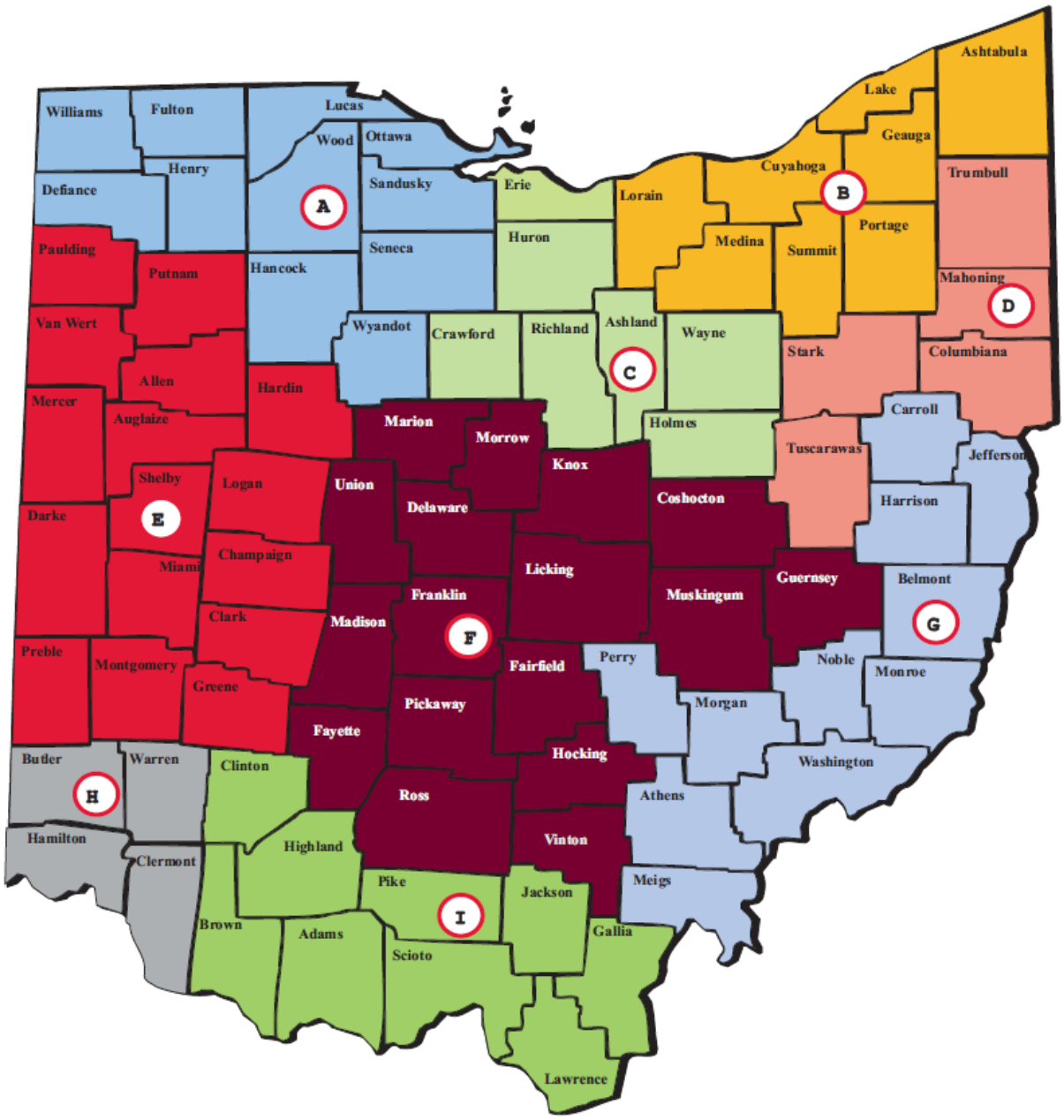

Figure 2. Ohio Labor Market Areas, by Ohio Department of Jobs and Family Services

Table 1. Descriptive Statistics for Male Apprentices, Ages between 18 and 24

	Full Sample		Completers		Dropouts	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Age	21.215	1.868	21.317	1.859	21.094	1.872
White	0.865	0.341	0.892	0.311	0.834	0.372
Hispanic	0.020	0.140	0.022	0.147	0.018	0.133
Black	0.054	0.227	0.029	0.168	0.084	0.278
Other race	0.069	0.253	0.065	0.247	0.072	0.259
Veteran	0.033	0.178	0.028	0.164	0.039	0.194
High school dropouts	0.028	0.165	0.018	0.132	0.040	0.196
High school graduates	0.927	0.260	0.939	0.239	0.913	0.282
Education info missing	0.045	0.207	0.043	0.203	0.047	0.212
Earnings 6-9 years after program participation	47613	27277	58324	24249	34298	24861
Earnings 6 years after program participation	45527	26047	56703	22968	32324	23129
Earnings 7 years after program participation	47317	26917	58204	23593	33708	24520
Earnings 8 years after program participation	48850	28301	59413	24681	35636	26963
Earnings 9 years after program participation	51310	27875	61744	25264	38161	25338
Earnings 1 year before program participation	14889	12934	17213	13536	12143	11600
Earnings 2 years before program participation	10759	11954	12483	12687	8721	10674
Number of quarters being employed before program participation	12.733	8.297	13.727	8.503	11.559	7.887
Years stayed in the program	3.071	1.797	4.084	1.269	1.874	1.581
RTI credit (hours)	24.328	106.627	31.584	126.845	15.756	75.243
OJT credit (hours)	380.579	1052.926	502.060	1242.498	237.101	746.335
Program length (hours)	7684.937	1841.960	7823.975	1962.178	7520.723	1674.497
Program start hourly wage	11.895	3.927	12.568	3.384	11.101	4.357
Program exit hourly wage	19.545	8.173	24.942	6.262	13.174	4.939
Union status	0.667	0.471	0.714	0.452	0.611	0.488
N	6,712		3,348		3,077	

Notes: RTI credit is the related technical instruction hours waived for a given apprentice, based on his previous learning. OJT credit is the on-the-job training hours waived for a given apprentice. N represents the number of people in our sample. Our sample only includes individuals who have positive post-program earnings.

Table 2. Descriptive Statistics for Male Ages between 18 and 24, WIA Participants and Apprentices

	Full Sample		WIA Participants		Apprentices	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Age	20.706	1.896	20.309	1.821	21.215	1.868
White	0.658	0.474	0.495	0.500	0.865	0.341
Hispanic	0.028	0.165	0.034	0.182	0.020	0.140
Non-white non-Hispanic	0.278	0.448	0.406	0.491	0.114	0.318
Race missing	0.036	0.187	0.064	0.245	0	0
Veteran	0.020	0.141	0.011	0.102	0.033	0.178
High school dropouts	0.178	0.383	0.296	0.456	0.028	0.165
High school graduates	0.802	0.398	0.704	0.456	0.927	0.260
Education info missing	0.020	0.139	0	0	0.045	0.207
Earnings 6-9 years after program participation	33371	26391	22328	19504	47613	27277
Earnings 6 years after program participation	31422	25260	20379	18133	45527	26047
Earnings 7 years after program participation	32753	25929	21901	18911	47317	26917
Earnings 8 years after program participation	34008	26889	23443	19979	48850	28301
Earnings 9 years after program participation	36224	27595	24939	21267	51310	27875
Earnings 1 year before program participation	9721	12109	5675	9653	14889	12934
Earnings 2 years before program participation	7661	11165	5237	9849	10759	11954
Number of quarters being employed before program participation	9.662	8.538	7.258	7.933	12.733	8.297
N	15,286		8,574		6,712	

Note: N represents the number of people in our sample.

Table 3. Earning Regressions, WIA Participants vs. Apprentices

Outcome variable: Log earnings six to nine years after program entry						
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Apprentice	1.034*** (0.023)	1.057*** (0.023)	0.518*** (0.022)	0.392*** (0.023)	0.649*** (0.026)	0.326*** (0.023)
Age	-	-	-	-0.041 (0.056)	-0.164*** (0.052)	-0.145*** (0.050)
Age Squared	-	-	-	0.001 (0.001)	0.002** (0.001)	0.002** (0.001)
Hispanics	-	-	-	0.022 (0.033)	0.015 (0.040)	0.065* (0.034)
Non-white Non-Hispanics	-	-	-	-0.222*** (0.018)	-0.380*** (0.022)	-0.173*** (0.018)
Veteran	-	-	-	-0.054 (0.055)	0.150** (0.070)	0.086 (0.060)
High School Dropouts	-	-	-	-0.373*** (0.027)	-0.452*** (0.027)	-0.317*** (0.025)
Log earning one year before entry	-	-	-	-	0.036*** (0.003)	0.027*** (0.002)
Log earning two years before entry	-	-	-	-	0.007** (0.003)	0.004* (0.002)
Work experience	-	-	-	-	0.023*** (0.002)	0.017*** (0.002)
Year FE	No	Yes	Yes	Yes	Yes	Yes
Labor Market FE	No	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No	Yes
$\boldsymbol{R^2}$	0.146	0.157	0.324	0.340	0.238	0.358
N	50,381	50,381	50,381	50,381	50,318	50,381

Notes: Omitted categories are white and high school dropouts. Coefficients of race missing dummy and education missing dummy are not shown in the table. All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table 4. Earning Regressions, WIA Participants vs. Apprentices, Long-term Earnings for Different Cohorts

	2006-12 Cohort	2006-11 Cohort	2006-10 Cohort	2006-09 Cohort	2006-07 Cohort	2008-10 Cohort	2011-12 Cohort
Earnings six years after program entry	0.309*** (0.027)	0.300*** (0.028)	0.312*** (0.030)	0.333*** (0.035)	0.300*** (0.062)	0.311*** (0.037)	0.317*** (0.048)
Earnings seven years after program entry	-	0.279*** (0.033)	0.284*** (0.030)	0.315*** (0.033)	-	-	-
Earnings eight years after program entry	-	-	0.338*** (0.033)	0.328*** (0.033)	-	-	-
Earnings nine years after program entry	-	-	-	0.380*** (0.033)	-	-	-
N	15,286	13,280	11,281	9,396	4,632	6,729	3,925

Notes: Results in this table are from regressions using program entry ages 18-24 sample. All regressions control for labor market fixed effects, cohort fixed effects, and industry fixed effects. All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table 5. Earning Regressions, WIA Participants vs. Apprentices, Heterogeneity Tests

Outcome variable: Log earnings six to nine years after program entry		
Panel A: Whites Only		
	(1)	**(2)**
Apprentice	0.670*** (0.028)	0.342*** (0.027)
N	32,940	
Panel B: Non-whites Only		
	(1)	**(2)**
Apprentice	0.496*** (0.053)	0.204*** (0.053)
N	14,024	
Panel C: WIA vs. Apprenticeship Dropouts		
	(1)	**(2)**
Apprentice	0.258*** (0.028)	0.156*** (0.025)
N	38,186	
Panel D: WIA vs. Apprentices Who Stayed in Program Less Than One Year		
	(1)	**(2)**
Apprentice	0.222*** (0.039)	0.151*** (0.033)
N	32,178	
Panel E: WIA vs. Apprentices Whose Program Required Length Less Than Three Years		
	(1)	**(2)**
Apprentice	0.452*** (0.039)	0.267*** (0.033)
N	32,525	
Panel F: WIA vs. Apprentices Whose Program Required Length More Than Three Years		
	(1)	**(2)**
Apprentice	0.716*** (0.024)	0.386*** (0.024)
N	46,245	
Demographic Variables	Yes	Yes
Pre-program Labor Market Outcomes	Yes	Yes
Year FE	Yes	Yes
Labor Market FE	Yes	Yes
Cohort FE	Yes	Yes
Industry FE	No	Yes

Notes: All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table 6. Earning Regressions, Apprenticeship Completers vs. Dropouts, Ages 18-24 When Entered Apprenticeship Programs

Outcome variable: Log earnings six to nine years after entered the program					
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Completed	0.801*** (0.026)	0.540*** (0.027)	0.461*** (0.025)	0.449*** (0.025)	0.337*** (0.038)
Age	-	-	-	-0.167* (0.097)	-0.159 (0.099)
Age Squared	-	-	-	0.003 (0.002)	0.003 (0.002)
Black				-0.216*** (0.044)	-0.210*** (0.043)
Hispanics	-	-	-	0.010 (0.039)	0.012 (0.039)
Other race	-	-	-	0.005 (0.038)	0.007 (0.039)
Veteran	-	-	-	0.011 (0.054)	0.011 (0.054)
High School Dropouts				-0.080 (0.059)	-0.072 (0.058)
Log earning one year before entry	-	-	-	0.017*** (0.003)	0.018*** (0.003)
Log earning two years before entry	-	-	-	0.001 (0.003)	0.001 (0.003)
Work experience	-	-	-	0.008*** (0.002)	0.007*** (0.001)
Years stayed in the program	-	-	-	-	-0.020*** (0.007)
RTI credit	-	-	-	-	0.000 (0.000)
OJT credit	-	-	-	-	-0.000** (0.000)
Term length	-	-	-	-	0.000 (0.000)
Start wage	-	-	-	-	-0.000 (0.004)
Exit wage	-	-	-	-	0.016*** (0.002)
Union	-	-	-	-	-0.080** (0.032)
Year FE	No	Yes	Yes	Yes	Yes
Labor Market FE	No	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes
R^2	0.150	0.306	0.352	0.361	0.363
N	22,004	22,004	22,004	22,004	22,004

Notes: RTI credit is the number of related technical instruction hours waived for a given apprentice, based on his previous learning. OJT credit is the number of on-the-job training hours waived for a given apprentice. Omitted categories are white and high school graduates. Coefficient of education missing dummy variable is not shown in the table. All earnings are adjusted to 2018 price level. N represents the number of person-year observations in our sample Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table 7. Earning Regressions, Long-term Earnings, Apprenticeship Completers vs. Dropouts

	2006-12 Cohort	2006-11 Cohort	2006-10 Cohort	2006-09 Cohort	2006-07 Cohort	2008-10 Cohort	2011-12 Cohort
Earnings six years after program entry	0.320*** (0.045)	0.302*** (0.042)	0.308*** (0.044)	0.362*** (0.047)	0.414*** (0.052)	0.321*** (0.077)	0.120* (0.064)
Earnings seven years after program entry	-	0.350*** (0.056)	0.297*** (0.061)	0.304*** (0.076)	-	-	-
Earnings eight years after program entry	-	-	0.313*** (0.048)	0.284*** (0.051)	-	-	-
Earnings nine years after program entry	-	-	-	0.291*** (0.048)	-	-	-
N	6,704	5,660	4,685	4,014	2,595	2,174	1,935

Notes: Results in this table are from regressions using ages 18-24 when started the program sample. All regressions control for labor market fixed effects, cohort fixed effects, industry fixed effects, and occupation fixed effects. All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table 8. Apprenticeship Completers vs. Dropouts, Heterogeneity Tests

Outcome variable: Log earnings six to nine years after program entry			
Panel A: Whites vs. Non-Whites			
	White Only	**Non-White Only**	
Completer	0.329*** (0.040)	0.368*** (0.058)	
N	19,004	2,969	
Panel B: Joint Sponsored (Union) vs. Unilateral Sponsored (Non-Union)			
	Joint Sponsored Programs	**Unilateral Sponsored Programs**	
Completer	0.449*** (0.045)	0.198*** (0.049)	
N	15,061	6,912	
Panel C: Firm Size			
	Small Firms	**Medium Firms**	**Large Firms**
Completer	0.198*** (0.073)	0.393*** (0.052)	0.338*** (0.064)
N	5,154	12,185	4,634

Notes: All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. All regressions control for year fixed effects, labor market fixed effects, cohort fixed effects, industry fixed effects, and occupation fixed effects. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Appendix. Additional Tables and Figures

Table A.1. Descriptive Statistics for Apprentices, 2006-2012 Cohorts, Ages Between 18-56

	Full Sample		Completers		Dropouts	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Age	28.218	8.035	28.263	7.853	28.162	8.258
White	0.814	0.389	0.850	0.357	0.770	0.421
Hispanic	0.022	0.147	0.023	0.150	0.021	0.144
Black	0.101	0.302	0.067	0.250	0.145	0.352
Other race	0.073	0.259	0.070	0.256	0.075	0.264
Veteran	0.079	0.269	0.082	0.275	0.074	0.262
High school dropouts	0.031	0.174	0.019	0.136	0.047	0.212
High school graduates	0.923	0.267	0.937	0.243	0.905	0.293
Education info missing	0.046	0.209	0.044	0.206	0.048	0.214
Earnings 6-9 years after program participation	48346	29039	59764	26820	33444	24757
Earnings 6 years after program participation	46729	28126	58613	24909	31853	23709
Earnings 7 years after program participation	48125	28859	59625	26446	33001	24613
Earnings 8 years after program participation	49331	29621	60751	27238	34523	25782
Earnings 9 years after program participation	51168	29571	62468	27506	36334	25331
Earnings 1 year before program participation	21148	20316	25573	21520	15609	17163
Earnings 2 years before program participation	19091	20781	22839	21923	14398	18202
Number of quarters being employed before program participation	25.346	16.725	27.158	16.862	23.077	16.272
Years stayed in the program	2.950	1.794	3.812	1.425	1.871	1.617
RTI credit (hours)	37.812	135.767	51.906	164.866	20.167	83.208
OJT credit (hours)	649.766	1495.690	855.443	1741.046	392.300	1060.183
Program length (hours)	7444.349	2005.575	7688.041	2001.573	7139.297	1968.638
Program start hourly wage	12.270	4.978	13.496	4.312	10.735	5.318
Program exit hourly wage	19.584	8.849	24.979	6.785	12.835	6.057
Union status	0.654	0.476	0.717	0.451	0.574	0.494
N	16,610		9,234		7,376	

Notes: RTI credit is related technical instruction hours waived for a given apprentice, based on his previous learning. OJT credit is on-the-job training hours waived for a given apprentice. N represents the number of people in our sample. The sample only includes those who have positive post-program earnings.

Table A.2. Earning Regressions, WIA Participants vs. Apprentices, Different Cohorts

Outcome variable: Log earnings six to nine years after entered the program						
Panel A: Ages 18-24 when entered the program						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Apprentice	1.034*** (0.023)	1.057*** (0.023)	0.518*** (0.022)	0.392*** (0.023)	0.649*** (0.026)	0.326*** (0.023)
R^2	0.146	0.157	0.324	0.340	0.238	0.358
N	50,381	50,381	50,381	50,381	50,381	50,381
Panel B: Ages 25-34 when entered the program						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Apprentice	0.392*** (0.045)	0.421*** (0.044)	0.122*** (0.028)	0.085*** (0.024)	0.350*** (0.025)	0.137*** (0.019)
R^2	0.026	0.045	0.280	0.285	0.167	0.327
N	43,484	43,484	43,484	43,484	43,484	43,484
Panel C: Age 35 or older when entered the program						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Apprentice	0.192*** (0.038)	0.253*** (0.037)	0.138*** (0.028)	0.134*** (0.029)	0.327*** (0.028)	0.201*** (0.025)
R^2	0.004	0.029	0.234	0.251	0.143	0.286
N	57,164	57,164	57,164	57,164	57,164	57,164
Panel D: Ages 18-24 when entered the program, high school graduates only						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Apprentice	0.877*** (0.024)	0.913*** (0.023)	0.432*** (0.020)	0.376*** (0.022)	0.637*** (0.025)	0.311*** (0.023)
R^2	0.125	0.138	0.312	0.316	0.197	0.336
N	39,943	39,943	39,943	39,943	39,943	39,943
Demographic Variables	No	No	No	Yes	Yes	Yes
Pre-program Labor Market Outcomes	No	No	No	No	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes	Yes
Labor Market FE	No	Yes	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	No	Yes

Notes: All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table A.3. Earning Regressions, Apprenticeship Completers vs. Dropouts, Different Age Groups

Outcome variable: Log earnings six years after entered the program					
Panel A: Ages 18-24 when entered the program					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Apprentice	1.034*** (0.023)	1.057*** (0.023)	0.518*** (0.022)	0.392*** (0.023)	0.326*** (0.023)
R^2	0.150	0.306	0.352	0.361	0.363
N	22,004	22,004	22,004	22,004	22,004
Panel B: Ages 25-34 when entered the program					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Apprentice	0.972*** (0.027)	0.620*** (0.031)	0.493*** (0.032)	0.471*** (0.032)	0.356*** (0.036)
R^2	0.169	0.341	0.385	0.400	0.404
N	21,418	21,418	21,418	21,418	21,418
Panel C: Age 35 or older when entered the program					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Apprentice	0.892*** (0.049)	0.559*** (0.040)	0.453*** (0.041)	0.432*** (0.041)	0.403*** (0.054)
R^2	0.136	0.336	0.384	0.403	0.405
N	10,579	10,579	10,579	10,579	10,579
Demographic Variables	No	No	No	Yes	Yes
Pre-program Labor Market Outcomes	No	No	No	No	Yes
Year FE	No	Yes	Yes	Yes	Yes
Labor Market FE	No	Yes	Yes	Yes	Yes
Cohort FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
Occupation FE	No	No	Yes	Yes	Yes

Notes: All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table A.4. Long-term Earnings for Different Apprentices Cohorts, All Male Sample

	2006-12 Cohort	2006-11 Cohort	2006-10 Cohort	2006-09 Cohort	2006-07 Cohort	2008-10 Cohort	2011-12 Cohort
Earnings six years after program entry	0.411*** (0.046)	0.322*** (0.031)	0.334*** (0.038)	0.396*** (0.044)	0.444*** (0.067)	0.472*** (0.075)	0.267*** (0.046)
Earnings seven years after program entry	-	0.314*** (0.026)	0.293*** (0.029)	0.301*** (0.036)	-	-	-
Earnings eight years after program entry	-	-	0.356*** (0.034)	0.325*** (0.033)	-	-	-
Earnings nine years after program entry	-	-	-	0.366*** (0.032)	-	-	-
N	16,594	14,167	11,587	9,894	6,280	5,486	4,828

Notes: Results in this table are from regressions using ages 18-56 when started the program sample. All regressions control for labor market fixed effects, cohort fixed effects, industry fixed effects, and occupation fixed effects. All earnings are adjusted to 2018 price level. Figures in parentheses are standard errors robust to clustering at the labor market by cohort level. N represents the number of person-year observations in our sample. Significance is defined as follows: *** p<0.01; ** p<0.05; * p<0.10.

Table A.5. Number of Apprentices by Program Starting Year and Program Status

Program Starting Year	Dropped out	Completed	Still in program	Total
2006	2,399 (48.7%)	2,389 (48.5%)	136 (2.8%)	4,924
2007	2,752 (52.5%)	2,386 (45.4%)	108 (2.1%)	5,246
2008	2,354 (53.1%)	1,990 (44.9%)	86 (1.9%)	4,430
2009	1,410 (54.3%)	1,068 (41.1%)	118 (4.5%)	2,596
2010	1,323 (50.3%)	1,227 (46.6%)	81 (3.1%)	2,631
2011	2,041 (47.7%)	1,974 (46.2%)	262 (6.1%)	4,277
2012	2,363 (50.4%)	1,720 (36.7%)	609 (13.0%)	4,692
Total	14,642 (50.8%)	12,754 (44.3%)	1,400 (4.9%)	28,796

Note: The unit of analysis in this table is individual. In the analysis, we only use who were between ages 18-24 when entered the program and do not include those who are still in programs and those who do not have positive post-program earnings.