THE LONG-TERM IMPACT OF APPRENTICESHIP ON THE EMPLOYMENT OUTCOMES OF DISPLACED WORKERS

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ABSTRACT

This study evaluates the long-term impact of registered apprenticeship on workers displaced during the Great Recession in North Carolina. Unemployment insurance claimants who enrolled in an apprenticeship program after losing their job experienced improved employment and wage-earning outcomes that lasted at least nine years. Program enrollees earned an average of $9,691 more (in 2019 dollars) than a matched comparison group of non-participants in the ninth year following job displacement. This work contributes to the evaluation literature on registered apprenticeship in the United States and provides evidence on the effectiveness of apprenticeship as a workforce intervention during economic downturns.

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I. Introduction

The COVID-19 pandemic has led to record-high levels of job displacement in the United States.[1] Prolonged joblessness is growing more prevalent as the COVID-19 crisis continues and temporary layoffs turn into long-term unemployment spells.[2] These worsening conditions highlight the need for policymakers to identify programs and services that improve the employment and wage-earning outcomes of displaced workers in a recessionary environment. This study evaluates the impact of North Carolina's registered apprenticeship programs on the long-term outcomes of workers displaced during the Great Recession, providing evidence on the effectiveness of apprenticeship as a workforce intervention during an economic downturn.

Although apprenticeship programs are not necessarily targeted at workers displaced during recessions, they may be of particular benefit to this population. Jobless individuals are less likely to find work during periods of recession (Farber 2011), and those who endure longer periods of joblessness tend to have worse outcomes in the long run (Kaitz 1970, Berger-Gross et al. 2017). Protracted joblessness can harm displaced workers' employment prospects by discouraging them from continued job search (Krueger and Mueller 2011), eroding their skill levels (Edin and Gustavsson 2008), and providing an adverse signal to potential employers (Kroft et al. 2013). Unlike workforce programs that prolong displaced workers' jobless spells by "locking" them into unpaid training and reducing their labor market availability (Card et al. 2010, Heinrich et al. 2013), apprenticeship programs require individuals to obtain paid

[1] Nearly 6.9 million workers nationwide filed an initial claim for unemployment insurance during the week of March 28, 2020, almost ten times more than the previous record set during the 1981-1982 recession (U.S. Employment and Training Administration).

[2] The share of unemployed workers on temporary layoff in the United States fell from 78% in April 2020 to 26% in November 2020, while the median duration of unemployment increased from two weeks to 19 weeks (U.S. Bureau of Labor Statistics).

employment at a sponsoring employer before they can enroll. Paid work experience is an essential component of apprenticeship programs. Participants also gain skills and practical experience through on-the-job training and technical instruction. Those who complete the program are issued an occupational credential that serves as a beneficial signal to future employers. This combination of re-employment, training, and certification may counteract the factors that lead workers displaced during recessions to have poor employment outcomes in the long run.

The existing literature on apprenticeship programs in the United States offers limited but promising evidence of their long-term benefits. Hollenbeck and Huang (2016) find that registered apprentices see improved employment and wage-earning outcomes for at least seven quarters after completing the program, while Reed et al. (2012) report employment and wage gains that persist at least nine years following enrollment. However, these studies do not focus specifically on displaced workers. Other studies examine whether services that resemble particular elements of apprenticeship programs, such as subsidized employment (Woodbury and Spiegelman 1987, Gerfin et al., 2005) and occupational training (Decker and Corson 1995, Fitzenberger and Völter 2007), improve the outcomes of unemployed individuals, but we lack evidence on whether the combination of services offered by apprenticeship programs improves the post-displacement outcomes of this population.

This study follows a group of unemployment insurance claimants displaced between 2008 and 2010 who enrolled in a registered apprenticeship program in North Carolina after losing their job. Participation in an apprenticeship program led to economically meaningful long-term improvements in these workers' employment and wage-earning outcomes. The employment rate of program enrollees was 16.9 percentage points higher than a matched comparison group of

non-participants nine years following displacement. Among those who remained employed nine years after their initial displacement date, program enrollees earned an average of $7,201 more at their job than employed workers in the comparison group. Because individuals who enrolled in apprenticeship programs were more likely to find and maintain employment and, when they did so, took home higher wages, they earned more than non-enrollees overall: in the ninth year after job loss, program enrollees earned an average of $9,691 more than non-participants, regardless of their employment status. These findings are robust to various modeling approaches with different specifications and identifying assumptions.

The next section describes the data and methods used to estimate the impact of registered apprenticeship on displaced workers. Section III reports the main findings of this study as well as results from alternative models. Section IV concludes with a discussion of these findings, their limitations, and their implications for workforce development policy.

II. Data and Methods

a. Data

Data for this study are from the Common Follow-up System (CFS), a longitudinal repository of administrative microdata covering all participants in state and federally funded workforce and education programs in North Carolina. The CFS is maintained by a collaborative effort between the Government Data Analytics Center of the North Carolina Department of Information Technology and the Labor and Economic Analysis Division of the North Carolina Department of Commerce. Participating agencies are required by state law to contribute data to the CFS for program evaluation and other official purposes.[3]

[3] More information about the Common Follow-up System can be found here: https://tools.nccareers.org/CFS/

Registered apprenticeship data for this study are from the North Carolina Department of Labor, which housed the state apprenticeship agency during the study period.[4] These programmatic records are linked by participants' Social Security number (SSN) to quarterly wage-earning records provided by the state unemployment insurance (UI) program administrator, the Division of Employment Security of the North Carolina Department of Commerce (DES), to obtain employment and wage outcomes. Employers report wage information to DES to assess their UI tax liability and verify claimants' UI benefit eligibility. Although UI wage records represent an accurate accounting of the vast majority of formal employment in the state, they are limited to jobs covered by North Carolina's state UI program and thus may omit earnings from self-employment, federal government employment, out-of-state employment, and other non-covered work. Data on UI claiming activity, including the displacement date and demographic and geographic attributes of UI claimants, are also provided by DES. The industry sector of employment is determined by linking UI wage records to the state's Quarterly Census of Employment and Wages.

This study focuses on workers displaced between January 2008 and December 2010, a three-year period covering much of the Great Recession and its immediate aftermath. The study cohort consists of 531,207 displaced workers with attributes likely to correspond with active, in-state job search: North Carolina residents, aged 20 to 54, not attached to their previous employer, filing a new, intrastate UI claim, with UI-covered employment in North Carolina in the year prior to displacement, who satisfied the criteria to receive regular state UI benefits. For

[4] North Carolina's registered apprenticeship agency – ApprenticeshipNC – is currently housed at the North Carolina Community College System. More information about ApprenticeshipNC can be found here: https://www.apprenticeshipnc.com/

individuals filing multiple initial claims during the study period, the first displacement date is selected. The treatment group consists of 219 cohort members who enrolled in a registered apprenticeship program within one year after their displacement date. Treatment effects are obtained by comparing the average outcomes of the treatment group in each annual (four-quarter) period after displacement with a comparison group pulled from the same cohort. Individuals are recorded as "employed" if they had any wage earnings during a given outcome year. Wage levels are adjusted to 2019 dollars using the Consumer Price Index for All Urban Consumers. Registered apprenticeship data are self-reported by sponsoring employers, some of whom do not list the SSN of participants. This study includes only those displaced workers and program enrollees for whom we have valid SSNs, enabling the estimation of program impacts.[5]

The short-term employment impacts of registered apprenticeship are a direct consequence of how the program is structured. Since all participants engage in paid employment while enrolled in the program, we should expect them to have higher rates of employment and higher overall wage earnings than non-participants in the first year after displacement. The long-term impacts are assessed by estimating treatment effects through the ninth subsequent year. Most individuals who enroll in a registered apprenticeship program in North Carolina exit the program within two years; accordingly, the long-term treatment effects reported in this study represent the long-term impact of program enrollment and are not an artifact of ongoing participation in the program.[6]

[5] Social Security numbers are validated using the Social Security Administration validation criteria that were in effect during the study period: https://www.ssa.gov/employer/ssnvhighgroup.htm

[6] Forty-four percent of individuals who enrolled in a registered apprenticeship program in North Carolina between January 2008 and December 2011 successfully completed the program within eight years. Of these, 58% completed within two years and 91% completed within four years.

b. Methods

This study is conducted in a nonexperimental setting. Individuals enroll in registered apprenticeship programs through a non-random and multi-sided selection process. Unlike other workforce programs that are available to all displaced workers, apprenticeship programs require individuals to obtain employment at a sponsoring employer before they can enroll. The applicant must be motivated to actively pursue such a position on their own or in consultation with an intermediary, such as a caseworker or career advisor, and the sponsoring employer must decide that the applicant has the desired skills for the position. Estimates of the treatment effect are biased if the outcomes of interest are correlated with factors underlying selection into the program.

Causal identification of treatment effects in this setting is supported by research establishing that selection bias in nonexperimental workforce program evaluation is attenuated under certain conditions. Influential work from Heckman et al. (1999) demonstrates that bias in nonexperimental treatment effect estimates is limited when using high-quality data and consistent instrumentation to compare individuals with similar attributes located in the same local labor markets. Studies by Mueser et al. (2007), Cook et al. (2008), and Sauermann and Sternberg (2020) point to the efficacy of difference-in-difference designs and controls for pre-program performance in reducing bias. Meta-analyses by Greenberg et al. (2006) and Card et al. (2010) show that, in general, workforce program evaluations using nonexperimental comparison group designs have tended to produce similar results to those from randomized experiments.

There is no consensus approach to estimating nonexperimental treatment effects (Heckman et al. 2009, p.2081). All approaches confront the problem of selection bias in different ways and require different identifying assumptions. Accordingly, this study estimates the impact

of registered apprenticeship using six different models and reports a range of estimates to reflect this epistemic uncertainty. The first ("naïve") model obtains the average treatment effect (ATE) by simply comparing the mean outcomes of the treatment group of program enrollees to those of a comparison group consisting of all non-participants. This model can be interpreted as identifying the causal impact of apprenticeship under the strong assumption that selection into an apprenticeship program is exogenous for the pool of displaced workers examined here. This assumption is unlikely to hold given the potential for selection bias in this setting. Accordingly, the results from this naïve model are reported merely for illustrative purposes.

The second model incorporates multivariate regression adjustment to remove the influence of measured confounders on the estimated treatment effects, achieving identification under the assumption of conditional independence, i.e., assuming that selection into an apprenticeship program is independent of employment outcomes conditional on observed covariates. This model employs flexible specifications for an array of demographic, geographic, and economic variables that are likely to affect both selection into the treatment group and the outcomes of interest, following the recent literature on nonexperimental workforce program evaluation (Heinrich et al. 2013, Andersson et al. 2016, Hollenbeck and Huang 2016). Demographic variables in this model include gender, race/ethnicity, and age at the displacement date, all of which are correlated with selection into the program and are predictive of post-displacement employment outcomes.[7] Indicator variables for individuals' year of displacement and county of residence at the time of displacement are included to control for temporal and

[7] Gender categories are male and female. Race/ethnicity categories are White, Black, Asian, Native American, Hispanic (regardless of race), and other/unknown. Age categories are specified in five-year increments: 20-24, 25-29, 30-34, 35-39, 40-44, 45-49, and 50-54.

geographic differences in labor market context and the availability and take-up of apprenticeship positions.[8] Controls for pre-displacement work history, including employment, wage earnings, employee tenure, and industry of employment, serve as proxies for individuals' job- and industry-specific human capital, motivation to pursue gainful employment, and attachment to the labor market in North Carolina.[9]

The third model uses a difference-in-difference approach that compares the change in outcomes between the pre- and post-displacement period for the treatment group versus the comparison group. This approach identifies the average treatment effect under the assumption that selection into the program is independent conditional on all factors that are stable over time. Another way to express this assumption is that, absent the treatment, the outcomes of the treatment and comparison groups would have increased or decreased over time at the same rate. If this assumption holds, this approach effectively controls for all time-invariant confounders, whether observable or unobservable.

The remaining models estimate the average treatment effect on treated individuals (ATT) using propensity score-matched comparison groups. This approach relies on the conditional independence assumption but is more robust than regression-based statistical adjustments, which can be sensitive to assumptions about functional form and perform poorly in the presence of large differences in covariate values between treatment and comparison groups (Rosenbaum and

[8] Indicator variables are included for each year of displacement covered in this study (2008, 2009, and 2010) and each of North Carolina's 100 counties as well as an indicator for unknown county of residence.

[9] Employment is specified as indicator variables for each of the four years preceding displacement. Real wage earnings and the square of real wages in each of the four years preceding displacement are also included as controls. Tenure is specified as four categories indicating the number of consecutive years an individual worked for the firm that was their primary employer in the first year preceding displacement (one year, two years, three years, or four or more years). Indicator variables for the industry sector of individuals' primary employer in the first year preceding displacement are coded at the 2-digit NAICS sector level.

Rubin 1983). However, because it is based on a comparison to a limited subset of non-participants that closely resemble program enrollees, this approach is less generalizable than approaches that incorporate the full population of non-participants. A logistic regression model predicting the likelihood of selection into an apprenticeship program is estimated to obtain propensity scores, using the same conditioning variables as listed above. The matched comparison group is assigned using one-to-one nearest-neighbor matching on the estimated propensity score, with an exact match on the county of residence to ensure treated and comparison individuals are located in the same local labor markets (Heckman et al., 1999). For the estimates of wage impacts among those who find work following displacement, separate comparison groups containing only employed workers are assigned for each outcome year.

The fourth model obtains the ATT by comparing the mean outcomes of the treatment group to those of the matched comparison group. The fifth model combines propensity score matching with regression adjustment to correct for bias resulting from any covariate imbalance that remains after matching (Abadie and Imbens 2011). The sixth model estimates the difference-in-difference treatment effect using matched comparison groups, controlling for any unobserved time-invariant confounders that remain after matching (Smith and Todd 2005).

The results from model #4, a univariate comparison of the treatment and matched comparison groups, are reported in section IIIa ("main findings"). This model represents the preferred model for this study due to its elegance and ease of interpretation by nontechnical stakeholders, such as workforce practitioners and policymakers, who are the target audience for

this research.[10] Results for all models, representing a range of findings under different specifications and identifying assumptions, are reported in section IIIb.

c. Descriptive statistics and covariate balance

For illustration, Table 1 compares the composition of the treatment group of apprenticeship program enrollees with non-participants along a handful of key observed characteristics. Individuals in the treatment group were substantially more likely to be white, male, under the age of 35, and employed in the construction sector prior to displacement, and less likely to live in one of North Carolina's four most populous counties,[11] than the full group of non-participants.

Covariate balance between the treatment and comparison groups is assessed using the standardized bias for each characteristic at the conventional 0.25 and 0.10 levels.[12] Covariate values for the full group of non-participants are poorly balanced with respect to the treatment group: of the 152 covariates used in this study, 12 are above the 0.25 threshold and 41 are above the 0.10 threshold of standardized bias. However, this very large pool of non-participants enables the assignment of a matched comparison group that is well-balanced with the treatment group along observed dimensions. The matching approach described above in section IIb yields a

[10] As noted by Rosenbaum and Rubin (1985, p.33): "One virtue, not the least important, of matched sampling is that nontechnical audiences often find that matching, when successful, is a persuasive method of adjusting for imbalances in observed covariates."

[11] These consist of Wake, Mecklenburg, Guilford, and Forsyth counties, which contain the cities of Raleigh, Charlotte, Greensboro, and Winston-Salem, respectively.

[12] Standardized bias is calculated as the absolute value of the mean difference between the treatment and comparison group divided by the standard deviation across all observations. Similar measures are commonly used to assess covariate balance between treatment and comparison groups (e.g., Rosenbaum and Rubin 1985).

comparison group with no covariates falling above the 0.25 threshold of standardized bias and only four crossing the 0.10 threshold.

Table 1: Selected descriptive statistics

	Treatment group	All non-participants	Standardized bias	Matched comparison group	Standardized bias
White	71%	57%	0.64	74%	0.01
Male	86%	54%	0.28	86%	0.07
Under age 35	58%	42%	0.33	61%	0.06
Construction sector	29%	11%	0.55	24%	0.10
Most populous counties	19%	30%	0.23	19%	0.00
Number of covariates above standardized bias threshold:					
0.25		12		0	
0.10		41		4	
Sample size	219	530,988		219	

Selected variables are shown for illustration purposes. The comparison group is matched on an array of demographic, geographic, and economic characteristics, including gender, race/ethnicity, age, year of displacement, county of residence, and pre-displacement employment, wage earnings, employee tenure, and industry of employment.

III. Results

a. Main findings

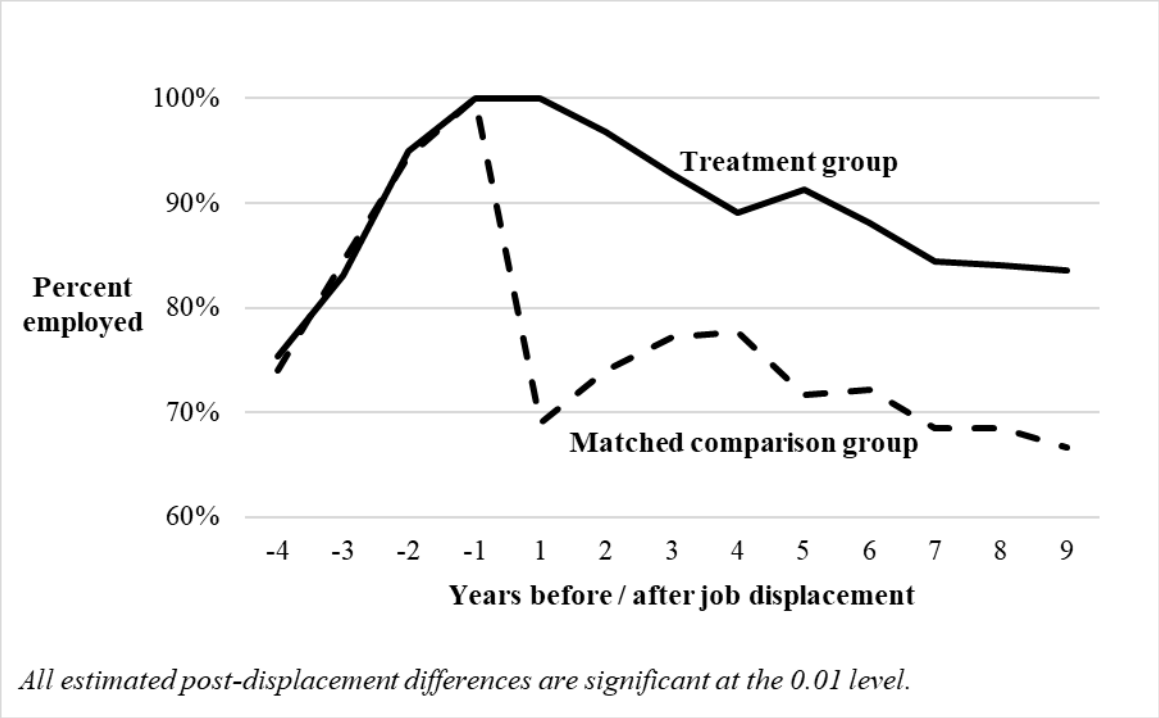
Figure 1 and Table 2 report the employment impact of registered apprenticeship programs in North Carolina using the preferred model. The treatment group and the matched comparison group had nearly identical rates of employment in the years prior to job displacement. All apprenticeship program enrollees found employment within one year after their displacement date, an artifact of participation in the program, while the employment rate of the comparison group dropped precipitously after displacement. The reported treatment effect of

.311 indicates that the employment rate of the treatment group was 31.1 percentage points higher than the comparison group in the first year after displacement.

Employment rates for both groups trended downward in subsequent years. This is a normal feature of longitudinal earnings data in North Carolina's UI wage records: workers tend to drop out of UI-covered employment over time as they migrate out of North Carolina, obtain non-UI covered work, or enter a spell of nonemployment.[13] However, program enrollees were more likely to remain employed than their counterparts throughout the post-displacement period, with an employment rate 16.9 percentage points higher than the comparison group in the ninth year following displacement.

[13] The employment rate of individuals working in North Carolina at any given point in time tends to decline around four percentage points in each subsequent year. For example, only 63% of individuals employed during the first quarter of 2008 could be found in North Carolina's UI wage records nine years later.

Figure 1: Employment rate



All estimated post-displacement differences are significant at the 0.01 level.

Table 2: Impact of registered apprenticeship on employment

Year after job displacement	Treatment effect	Standard error	T-value	
1	0.311	0.031	9.91	***
2	0.228	0.032	7.13	***
3	0.155	0.033	4.64	***
4	0.114	0.035	3.24	***
5	0.196	0.036	5.46	***
6	0.160	0.037	4.27	***
7	0.160	0.040	4.01	***
8	0.155	0.040	3.87	***
9	0.169	0.041	4.16	***

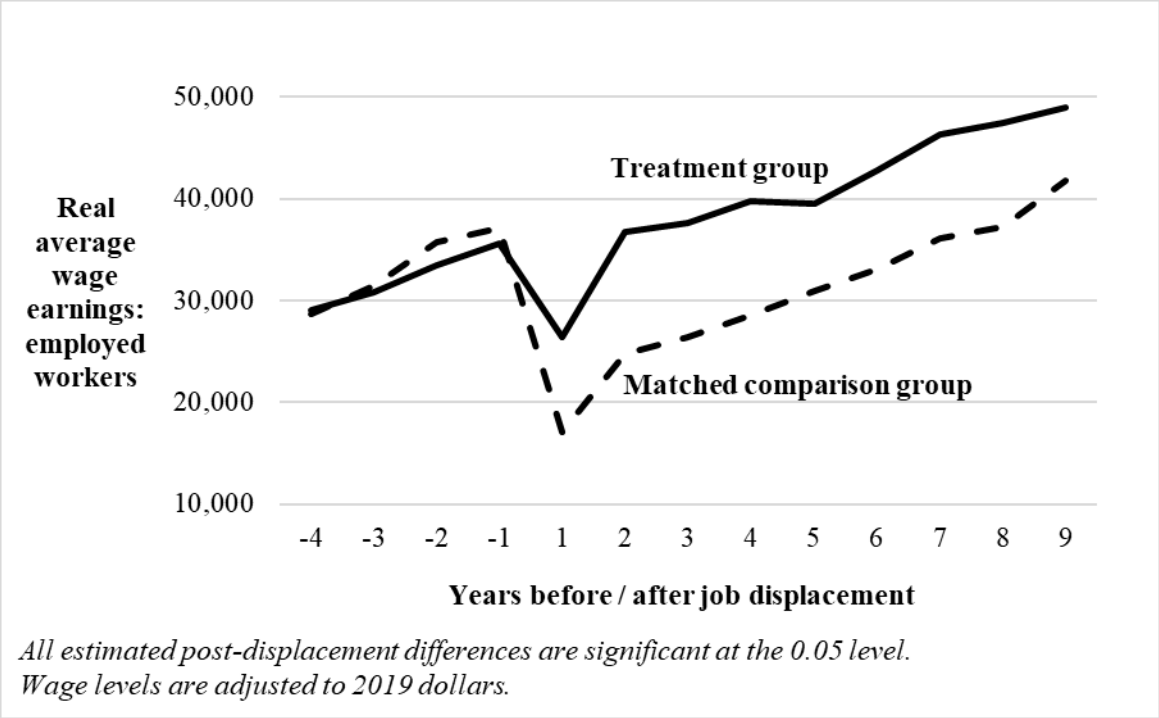
**** significant at the 0.01 level*

Figure 2 and Table 3 report the impact of apprenticeship on the wage earnings of those who found work. As with employment rates, the real average wage earnings of employed workers in the treatment and comparison groups diverged sharply in the first year, a gap that persisted in each year thereafter. Individuals who enrolled in an apprenticeship program and remained employed earned an average of $7,201 more than their counterparts in the ninth year after their displacement date. These impacts are estimated with somewhat less precision because only employed workers are considered here, resulting in a smaller sample size and fewer degrees of freedom than the other estimates.[14] Despite this, the estimated treatment effects remain significant at the 0.05 level in each outcome year.

Figure 3 and Table 4 report the impact of apprenticeship on real wage earnings for all individuals, regardless of their employment status. Again, we see a pattern of sharply diverging outcomes between the treatment and comparison groups in the first year after displacement, with apprenticeship program enrollees earning higher wages in each subsequent year. Overall, program enrollees earned an average of $9,691 more than their counterparts in the ninth year following displacement due to having both higher rates of employment and higher wage earnings conditional on employment.

[14] The sample size for these comparisons declines from 435 in the first year to 364 in the ninth year following displacement.

Figure 2: Real average wage earnings of employed workers



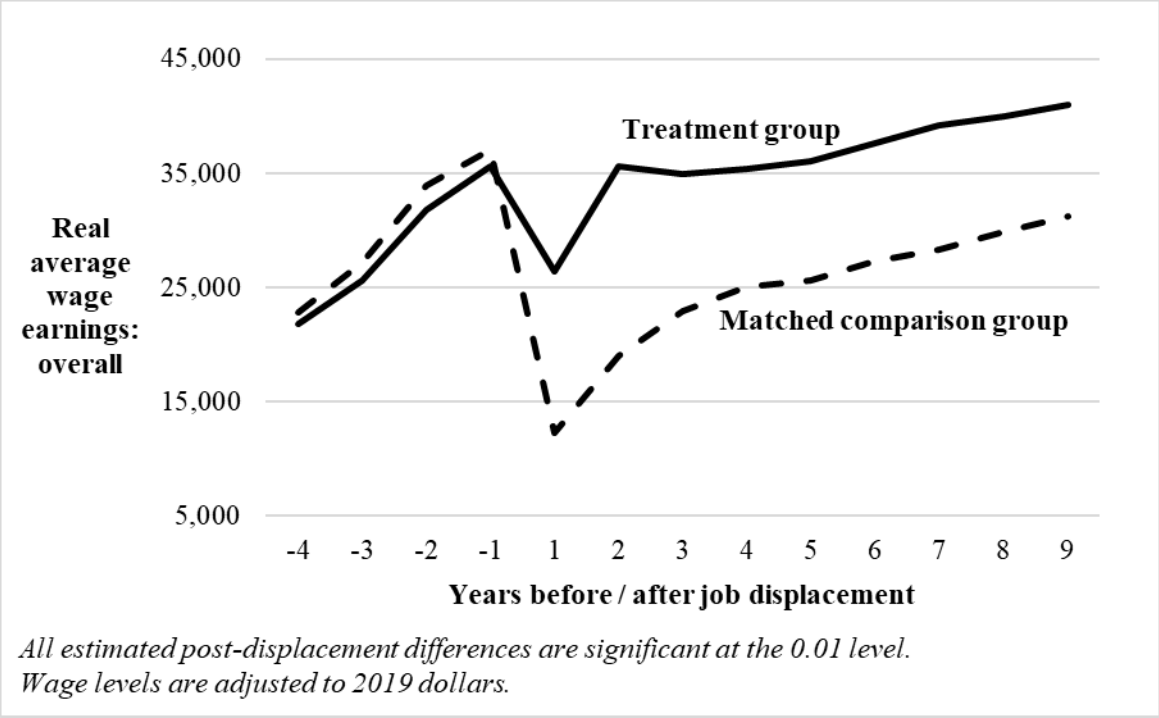
All estimated post-displacement differences are significant at the 0.05 level.
Wage levels are adjusted to 2019 dollars.

Table 3: Impact of registered apprenticeship on real wage earnings of employed workers

Year after job displacement	Treatment effect	Standard error	T-value	
1	9,258	1,272	7.28	***
2	12,085	1,625	7.44	***
3	11,228	1,842	6.10	***
4	11,255	1,948	5.78	***
5	8,588	2,042	4.21	***
6	9,717	2,323	4.18	***
7	10,278	2,589	3.97	***
8	10,258	2,513	4.08	***
9	7,201	3,182	2.26	**

**** significant at the 0.01 level*
*** significant at the 0.05 level*
Wage levels are adjusted to 2019 dollars.

Figure 3: Real average wage earnings (overall)



All estimated post-displacement differences are significant at the 0.01 level.
Wage levels are adjusted to 2019 dollars.

Table 4: Impact of registered apprenticeship on real wage earnings (overall)

Year after job displacement	Treatment effect	Standard error	T-value	
1	14,028	1,426	9.84	***
2	16,668	1,831	9.10	***
3	11,999	2,062	5.82	***
4	10,331	2,175	4.75	***
5	10,489	2,386	4.40	***
6	10,339	2,574	4.02	***
7	10,818	2,833	3.82	***
8	10,015	3,001	3.34	***
9	9,691	3,071	3.16	***

**** significant at the 0.01 level*
Wage levels are adjusted to 2019 dollars.

b. Full results

Tables 5, 6, and 7 report the impact of registered apprenticeship on employment, the wage earnings of employed workers, and overall wage earnings, respectively, estimated using all six models. The study findings are robust across these approaches, despite their different specifications and different identifying assumptions. All models generate impact estimates in each year following displacement that are positive and statistically significant. The matched comparison group estimates of the ATT (models #4, 5, and 6) are smaller than the ATE estimates using the full group of nonparticipants (models #1, 2, and 3), with the main findings (model #4) representing a lower bound of the overall wage impacts. Nonetheless, the estimated impacts are economically meaningful across all models and in all outcome years.

Table 5: Full results, employment impact of registered apprenticeship

	Model #					
	1	**2**	**3**	**4**	**5**	**6**
Year after job displacement	**Treatment effect**					
1	0.304	0.316	0.318	0.311	0.306	0.309
2	0.293	0.301	0.307	0.228	0.217	0.227
3	0.216	0.225	0.230	0.155	0.148	0.154
4	0.188	0.196	0.202	0.114	0.101	0.113
5	0.223	0.231	0.237	0.196	0.188	0.195
6	0.202	0.210	0.216	0.160	0.154	0.159
7	0.176	0.184	0.191	0.160	0.153	0.159
8	0.184	0.192	0.198	0.155	0.143	0.154
9	0.193	0.200	0.208	0.169	0.156	0.168
Comparison group:						
All non-participants	X	X	X			
Matched non-participants				X	X	X
Regression adjustment		X			X	
Difference-in-difference			X			X

All estimates are significant at the 0.01 level.

Table 6: Full results, wage impact of registered apprenticeship on employed workers

	Model #					
	1	**2**	**3**	**4**	**5**	**6**
Year after job displacement	**Treatment effect**					
1	9,676	9,435	10,268	9,258	9,036	10,382
2	13,129	12,236	13,721	12,085	11,982	13,210
3	10,773	9,958	11,364	11,228	10,235	12,352
4	10,662	9,496	11,253	11,255	10,578	12,379
5	8,443	6,910	9,035	8,588	7,796	9,712
6	9,583	7,383	10,175	9,717	9,624	10,842
7	11,159	8,602	11,751	10,278	11,504	11,402
8	10,907	8,028	11,499	10,258	10,043	11,382
9	11,336	8,277	11,928	7,201	6,847	8,326
Comparison group:						
All non-participants	X	X	X			
Matched non-participants				X	X	X
Regression adjustment		X			X	
Difference-in-difference			X			X

All estimates are significant at the 0.05 level.
Wage levels are adjusted to 2019 dollars.

Table 7: Full results, wage impact of registered apprenticeship (overall)

	Model #					
	1	2	3	4	5	6
Year after job displacement	Treatment effect					
1	14,748	14,659	15,741	14,028	14,366	15,566
2	19,638	19,098	20,632	16,668	16,812	18,206
3	15,798	15,180	16,792	11,999	12,340	13,537
4	14,969	14,228	15,963	10,331	10,370	11,869
5	14,626	13,769	15,619	10,489	10,976	12,026
6	15,130	14,104	16,123	10,339	11,170	11,877
7	15,640	14,326	16,633	10,818	11,344	12,356
8	15,904	14,318	16,897	10,015	10,465	11,553
9	16,760	15,054	17,754	9,691	10,099	11,229
Comparison group:						
All non-participants	X	X	X			
Matched non-participants				X	X	X
Regression adjustment		X			X	
Difference-in-difference			X			X

All estimates are significant at the 0.01 level.
Wage levels are adjusted to 2019 dollars.

IV. Discussion

This study demonstrates that registered apprenticeship can be an effective workforce intervention during economic downturns. North Carolina workers displaced during the Great Recession who enrolled in a registered apprenticeship program after losing their job experienced improved employment and wage-earning outcomes that lasted through at least the ninth year following their displacement date. The share of program enrollees employed during the ninth year following displacement was 16.9 percentage points higher than a matched comparison group of non-participants, with alternative models (other than the naïve model) generating

estimates that range between 15.6 and 20.8 percentage points. Among those who remained employed, program enrollees earned $7,201 more than non-participants in the ninth year following displacement, with alternative estimates ranging from $6,847 to $11,928. Overall, program enrollees earned $9,691 more than non-participants in the ninth year following displacement, with alternative estimates ranging from $10,099 to $17,754.

This study identifies the causal impact of registered apprenticeship on employment outcomes under a variety of assumptions, utilizing modeling approaches that have been shown to reduce the influence of selection bias on nonexperimental treatment effect estimates. However, the potential for unaddressed selection bias in this study cannot be fully ruled out. The matched and regression-adjusted estimates may be biased in the presence of unmeasured confounders, such as unobserved skill, and the difference-in-difference estimates may fail to capture influential time-varying factors, such as a change in motivation following displacement. The potential direction of any remaining selection bias on these findings is ambiguous. Additional research with randomized designs or natural experiments that exploit plausibly exogenous variation in program enrollment may be needed to further validate these findings.

The use of UI wage records in this study represents both a strength and a potential weakness. This type of dataset provides an accurate and comprehensive accounting of individuals' employment histories and is commonly used in evaluations of workforce programs in the United States. However, these data are limited in scope to employment covered by state UI law. The most glaring omission in these data is a lack of information about out-of-state employment. An average of 1.6% of Americans moved between states in each year during the study period, with unemployed workers migrating at more than double the rate of the broader population (U.S. Census Bureau). The program impacts reported in this study may be biased

upward if non-participants were systematically more likely to leave North Carolina after job displacement than program enrollees. This is a weakness that is shared by much of the evaluation literature on workforce programs. This study attempts to account for attachment to the North Carolina labor market by including only intrastate UI claimants in the study cohort and controlling for in-state work history prior to displacement. Any remaining differences in interstate mobility would have to be implausibly large to account for the employment impacts reported here.

Although this study finds that registered apprenticeship has a positive impact on the long-term employment outcomes of displaced workers, it offers little clarity about the causal mechanisms underlying this impact. Are there specific elements of registered apprenticeship that are particularly effective in assisting the unemployed? Or is the full suite of services offered by these programs necessary to produce the outcomes documented here? All displaced workers in this study who enrolled in a registered apprenticeship program were employed in the first year after their initial job displacement, compared to only 69% of the matched comparison group. Given the well-documented correlation between individuals' duration of joblessness and their subsequent outcomes, the effect of this re-employment may be sufficient to explain the long-term impacts reported here. However, it is likely that other aspects of registered apprenticeship—such as on-the-job training, technical instruction, and, for those successfully completing the program, a credential certifying occupational proficiency—also helped advance the career trajectories of program enrollees. It remains an open question whether registered apprenticeship programs as currently constituted are necessary to produce the positive impacts reported here or if the "secret sauce" of apprenticeship can be replicated by other workforce interventions that combine the "ingredients" of re-employment, training, and certification within the same program.

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