WORK, EDUCATION, AND LABOR

The Impact of Registered and Unregistered Apprenticeship

Evidence from the Scaling Apprenticeship and Closing the Skills Gap Grants

Jonah Deutsch
Mathematica

Daniel Kuehn
Urban Institute

Karen Gardiner
Urban Institute

Deborah Reed
Mathematica

Julia Payne
Urban Institute

Moriah Macklin
Urban Institute

Ariella Spitzer
Mathematica

Peter Schochet
Formerly Mathematica

Astrid Harnack-Eber
Formerly Mathematica

Peter Kress
Mathematica

URBAN INSTITUTE

RESEARCH REPORT

September 2025

DISCLAIMER

This report was prepared for the U.S. Department of Labor (DOL), Chief Evaluation Office (CEO) by the Urban Institute, under contract number 1605DC-18-A-0032/1605C2-21-F-00029. 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.

ACKNOWLEDGMENTS

The authors thank key members of the project team, including Barbara Butrica, Pam Loprest, Demetra Nightingale, and Samina Sattar. They are also grateful to Brett Fischer for contributing to the analysis; Gabby Foster, Matthew Martinez, Evan Morier, Owen Hart, and Liz Potamites for cleaning and analyzing data; and Sheldon Bond, Margaux Lieser, and Ryan Ruggiero for their efforts to collect state and college data. They thank Jill Berk for providing feedback on drafts of this report. Finally, the authors extend their deep gratitude to the staff at state workforce agencies, colleges, grantees, DOL, and the U.S. Department of Health and Human Services Office of Child Support Services National Directory of New Hires staff for providing the data that made this study possible.

ABOUT THE URBAN INSTITUTE

The nonprofit Urban Institute is a leading research organization dedicated to developing evidence-based insights that improve people's lives and strengthen communities. For 50 years, Urban has been the trusted source for rigorous analysis of complex social and economic issues; strategic advice to policymakers, philanthropists, and practitioners; and new, promising ideas that expand opportunities for all. Our work inspires effective decisions that advance fairness and enhance the well-being of people and places.

ABOUT MATHEMATICA

Mathematica is the insight partner that illuminates the path to progress for public- and private-sector changemakers. We apply expertise at the intersection of data, methods, policy, and practice, translating big questions into deep insights that weather the toughest tests. Driven by our mission to improve public well-being, we collaborate closely with our clients to improve programs, refine strategies, and enhance understanding.

Contents

Glossary

Incumbent worker: An individual who is employed but needs training to upgrade their skills to secure full-time employment, advance in their careers, or retain their current occupations in H-1B occupations and industries. Incumbent workers are workers who typically are employed in lower-skilled, lower wage, front-line, and/or entry-level positions, and where attaining new skills and competencies could help advance them into middle- and high-skilled jobs with their current employer.

Institution of higher education (IHE): Generally, a two-year or four-year college or university. For purposes of the grants, applicants had to represent a consortium of institutions of higher education, as defined in Section 102 of the Higher Education Act of 1965 (20 U.S.C. 1002) or be a state system of higher education, such as a community college system office or a single state higher educational board.

Mentor: Provides on-the-job training opportunities for apprentices. Mentors are typically other employees of the hiring employer who are already fully proficient in the occupation being learned by the apprentice.

Occupation, occupational field: The specific job associated with an apprenticeship program. The U.S. Department of Labor Office of Apprenticeship or a State Apprenticeship Agency (SAA), which assigns the job a distinct occupational code, must approve occupational fields. Grantees can operate multiple apprenticeship programs within an occupational field, and sponsors can operate multiple programs across different fields.

On-the-job training (OJT): Every apprenticeship program includes OJT (called "on the job learning" in apprenticeship regulations and OJT in the funding announcement). Apprentices get hands-on training from an experienced mentor at the job site for typically not less than one year. Structured OJT experiences are developed by mapping the skills and knowledge that the apprentice must learn over the course of the program to be fully proficient at the job. Employers traditionally bear most training related costs.

Pre-apprenticeship program: Prepares individuals to enter and succeed in an apprenticeship program through a training curriculum based on industry standards. Can include educational and pre-occupational services (e.g., career and industry awareness workshops, job readiness courses), hands-on training in simulated lab experience or through volunteer opportunities, and assistance in applying to apprenticeship programs. Pre-apprenticeship programs involve formal partnerships with at least one apprenticeship program sponsor.

Registration Agency: The U.S. Department of Labor Office of Apprenticeship or a federally recognized State Apprenticeship Agency (SAA) act as a Registration Agency, responsible for evaluating an apprenticeship program's apprenticeship standards and for ongoing evaluation of apprenticeship programs to determine whether they comply with federal regulations related to program design, worker protections, and other criteria. Registered programs can access federal resources, state tax credits where available, and technical assistance.

Registered apprenticeship program (RAP): A paid, structured program of work-based learning under mentors, providing both value to employers and formal technical instruction to workers, and culminating in an industry-recognized credential that meets standards for registration by a Registration Agency. The DOL Office of Apprenticeship recommends that a registered apprenticeship program includes at least 144 hours per year of related technical instruction and requires at least 2,000 hours of on-the-job training. An apprenticeship sponsor for a specific occupation runs the training program. Sponsors are responsible for registering individual apprentices and determining whether they have successfully completed the apprenticeship program.

Registered apprenticeship program addition, expansion, maintenance, or revision: Changes to an existing registered apprenticeship program, including the development of programs in additional occupational fields by an existing apprenticeship sponsor. Maintenance or expansion may also entail transitioning from a time-based apprenticeship to a competency-based or a hybrid apprenticeship.

Related technical instruction (RTI): Instruction that complements the apprentice's on-the-job learning, delivering the technical concepts and workforce and academic competencies needed to succeed on the job. A community college, a technical school, an apprenticeship training school, or the employer itself can provide the instruction. Education partners collaborate with employers to design the curriculum to deliver the skills and knowledge needed by apprentices. All partners work together to identify how to pay for the RTI, including the cost to the employer and other funds that can be leveraged.

Sponsor: Entity responsible for the overall operation of the registered apprenticeship program, working in collaboration with the partners. Sponsors can be a single employer or a consortium of employers. Alternatively, the sponsor can be any of a range of workforce intermediaries including an industry association or a joint labor-management organization. Community colleges and community-based organizations can also serve as sponsors.

Joint program: A program sponsored jointly by a labor organization and one or more employers

Non-joint program: A program not sponsored by a joint labor management organization

Group program: A program with one sponsor where multiple employers agree to the apprenticeship standards

Independent or nongroup program: A program with one sponsor and one employer

Standards of Apprenticeship: Document describing apprenticeship components for a specific job role. Its individual standards include the purpose of the proposed apprenticeship program, the term of the apprenticeship, the provision of related technical instruction, wage progression for the apprenticeship, supervision of apprentices, safety, registration of apprentices, work process schedule, probation period, periodic evaluation of apprentices' performance, completion requirements, and apprentice/mentor ratio.

Unregistered apprenticeship program: Includes paid work-based learning, on-the-job training, an educational or instructional component, and an industry-recognized credential on completion. Unlike registered programs, unregistered programs do not have sponsors or Standards of Apprenticeship that are recognized under the National Apprenticeship Act and are not directly reviewed and approved by federal or state apprenticeship offices.

Executive Summary

Apprenticeship is an "earn and learn" employer-based training model. Apprenticeships combine classroom-based instruction with on-the-job training (OJT) under a mentor at the employer's worksite. Apprentices are employed during their training and earn progressively higher wages. Traditionally used as a training model for construction-related occupations, the U.S. Department of Labor (DOL) aims to expand apprenticeships to a range of nontraditional occupations and to increase opportunities for all Americans through its grant programs. This report describes the impact of two federally funded apprenticeship grant programs on apprentices' employment and earnings nine quarters after enrolling: Scaling Apprenticeship through Sector-Based Strategies (Scaling Apprenticeship), and Apprenticeships: Closing the Skills Gap (Closing the Skills Gap). Between these two grant programs, DOL awarded almost $284 million to 51 grantees between 2019 and 2020. Box ES.1 provides a summary of these grant programs.

> BOX ES.1
>
> **Scaling Apprenticeship Grants**
>
> - Awarded in June 2019 to 23 grantees; grants ranged from $2 million to $12 million.
> - Only institutions of higher education (IHEs) were eligible to apply.
> - The average grantee proposed to serve 3,583 participants and 2,582 apprentices.
> - Grantees could support pre-apprenticeship programs.
>
> **Closing the Skills Gap Grantees**
>
> - Awarded in February 2020 to 28 grantees; grants ranged from about $2 million to $6 million. Three grants ended early and are not included in the study.
> - IHEs, industry or employer associations, labor unions, and workforce intermediaries could apply.
> - The average grantee proposed to serve 3,402 participants and 3,119 apprentices.
> - Grantees could not support pre-apprenticeship programs with grant funds.

Scaling Apprenticeship and Closing the Skills Gap grants had similar goals: expanding apprenticeships in industries and occupations with a high demand for skilled workers, and increasing apprenticeship opportunities generally. Both grant programs focused on occupations common in three industries: advanced manufacturing, information technology (IT), and health care. Closing the Skills Gap grantees had an added goal of expanding apprenticeship in artificial intelligence- and cybersecurity-related occupations, typically within the larger IT industry. Both grants had a four-year period of performance. Both programs supported creating new and expanding existing apprenticeship programs.

Grantees could focus on registered apprenticeship programs, which are approved by either the DOL Office of Apprenticeship (OA) or a federally recognized State Apprenticeship Agency (SAA), or unregistered programs. All grant-supported apprenticeship programs, regardless of registration status, had to include the following elements: paid, work-based learning at an employer site; OJT and mentorship; an educational or instructional component; an industry-recognized credential upon completion; and safety and supervision policies and procedures. Registered programs adhere to guidelines around the length of related technical instruction (RTI) and OJT. A sponsor is responsible for the program and maintains the Standards of Apprenticeship, which documents RTI, OJT, wage increases, and other aspects of the program. Unregistered programs are not required to have a sponsor or Standards of Apprenticeship. They do not have a 2,000 OJT hour minimum, so may be shorter than registered apprenticeships.[1]

Prior research found the positive impact of participating in apprenticeship on apprentice earnings and employment outcomes (Dula 2021; Hollenbeck and Huang 2016; Reed et al. 2012; Jacoby and Haskins 2020). This study adds to the evidence base on the impact of participating in apprenticeship programs outside of traditional construction occupations, the impact of participating in unregistered apprenticeship programs, as well as the impacts of participating for subgroups of apprentices.

Impact Study

The DOL Chief Evaluation Office (CEO) commissioned an evaluation of the Scaling Apprenticeship and Closing the Skills Gap grant programs. This report presents the results of the impact study. The purpose of the impact study is to estimate the effect of apprenticeship on employment and earnings.

Research Questions

The impact study research questions focus on the difference between the average outcomes of the apprentices and the average outcomes these individuals would have achieved if the grant programs did not exist.

The **primary impact study research questions** are:

- What is the impact of registered apprenticeships on earnings and employment of participants in the ninth quarter following program enrollment?

[1] DOL OA traditionally capitalizes “Registered Apprenticeship Program,” but we have chosen not to capitalize here to ensure uniformity between the terms “registered apprenticeship” and “unregistered apprenticeship.” Although expansion of registered apprenticeship is an important policy goal for DOL, registered apprenticeship was not preferred or privileged under the Scaling Apprenticeship and Closing the Skills Gap grant programs.

- What is the impact of unregistered apprenticeships on earnings and employment of participants in the ninth quarter following program enrollment?

The **secondary research questions** are:

- What are the impacts of registered and unregistered apprenticeships on ninth-quarter earnings and employment for different occupational sectors?
- What are the impacts of registered and unregistered apprenticeships on ninth-quarter earnings and employment for subgroups (sex, race/ethnicity, age, and incumbent worker status)?

The team selected the ninth quarter from program enrollment in the design phase of the study because many apprenticeship programs are two years or less and because, based on constraints imposed by the project timeline and the timing of data collection activities, it struck the best balance between being the longest duration (furthest in time from program enrollment) while providing a sufficiently large sample size for analysis.

Methods

To estimate the impact of participating in an apprenticeship, the evaluation used a quasi-experimental design (QED) to compare outcomes for apprenticeship participants with those of a matched comparison group of non-apprentices. Specifically, the evaluation team created two comparison groups that represent common workforce development pathways: (1) a sample of individuals who enrolled at a community college and trained in apprenticeship industries, and (2) a sample of individuals who received Wagner-Peyser Employment Services. We created these comparison groups to closely match the apprentices in our sample. Using and comparing two distinct comparison groups provides a more robust understanding of how apprenticeship outcomes compare to alternative pathways.

The impact study methods rely on a "selection on observables" assumption. Simply put, this assumption is based on the idea that observable characteristics can account for any key factors that relate to both enrolling in an apprenticeship program, and employment and earnings outcomes (see Imbens 2004 for a review of this methodology). The design adheres to principles for generating credible comparison groups for workforce development programs that are found in the literature (Heckman et al. 1998; Heckman, Ichimura, and Todd 1997; Glazerman, Levy and Meyers 2003). These are: selecting treatment and comparison groups from the same local areas so that they face the same local labor markets and service environments; using a set of socio-demographic variables from a common data source; and using preprogram earnings histories to capture pre-enrollment differences in employment and earnings that can influence later outcomes.

Data Sources

The impact evaluation relies on three main data sources. Each of these datasets, auxiliary data sources, and the methods for linking the data are described in more detail in the Technical Appendix.

- **Workforce Integrated Performance System (WIPS).**[2] These data include individual-level information about Scaling Apprenticeship and Closing the Skills Gap participants, as well as the Wagner-Peyser comparison group from nine states. DOL created the fields and definitions. Among other variables, the data contain demographic characteristics, employment status at program entry, highest education level completed at program entry, ex-offender status, low-income status, basic skills level, and program entry and exit dates.
- **Community College Data.** Community college data from eight states provides information on the community college comparison group and includes the same demographic characteristics as the WIPS data. Community college data also contain information on students' enrollment and course history.
- **National Directory of New Hires (NDNH).** The NDNH houses quarterly wage data provided by state unemployment insurance agencies and federal employment records. The study used NDNH data on employment and earnings to obtain pre-program earnings of apprentices and comparison group members, as well as to measure employment and earnings outcomes.

Caveats

Although the study attempts to address or mitigate threats to the validity of its findings in several ways, readers should consider the following:

- As with any QED study of a workforce program, there may be unobserved differences between apprentices and comparison group members that are associated with employment and earnings, despite using rigorous methods and rich data on pre-program earnings and

[2] WIPS is the performance management system for the Workforce Innovation and Opportunity Act, and for other DOL-funded workforce programs. Data are entered and updated quarterly for participants. For more information about WIPS data, including limitations, see: https://www.dol.gov/agencies/eta/performance/wips.

employment. However, this issue may be magnified with apprenticeship because, by definition, an employer hires an apprentice—either as a new hire or is a current employee (i.e., an incumbent worker). This poses an additional challenge since being in the treatment group means being selected by an employer and being employed as soon as enrollment takes place. Many of our sample restrictions and design choices aim to address this—using pre-program earnings, employment history, and other background characteristics—but unobserved differences between apprentices and comparison group members may remain.

- Apprenticeship programs vary in length—some last two years or less, others over three years. As a result, the ninth quarter after program entry represents a post-completion quarter for some apprentices but not for others. Impacts might have been higher or lower in a later quarter: some apprentices might have completed training and moved into higher-paying jobs, while for others, the impact may have faded. Similarly, some community college students may have been in longer-term programs, such as those planning to transfer to a four-year college. This could apply to some apprentices. The heterogeneity of apprenticeship program lengths introduces important interpretive challenges.
- The sample of apprentices used in the impact analysis may not be representative of the apprentices served by the grant programs, which themselves may not be representative of apprentices overall.

Summary of Findings

The overarching impact study finding is that registered and unregistered apprenticeships had large and significant impacts on employment and earnings in the ninth quarter post enrollment. This was true for apprentices when compared to both community college students and Wagner-Peyser participants. The study also found large and significant impacts on employment and earnings by occupational sector and apprentice subgroup.

These findings contribute to the growing evidence base on the value of employer-based training programs and confirm the effectiveness of apprenticeship—particularly outside of traditional construction occupations—as a viable pathway to higher-quality jobs. In contrast to many previous studies, our analysis draws on a geographically diverse sample across multiple states, enhancing the generalizability of the results. Additionally, we evaluate the impact of apprenticeship participation for all apprentices, not just those who complete their programs, providing a more comprehensive view of potential benefits. We also examine the outcomes associated with unregistered apprenticeship programs; however, these findings may not be generalizable to all unregistered programs because their design was shaped by criteria specified in the DOL funding announcement. Finally, our analysis includes subgroup estimates, offering insights into how the impact of apprenticeship varies across different populations. Together, these contributions offer new insights on the role of apprenticeship in today's workforce development landscape.

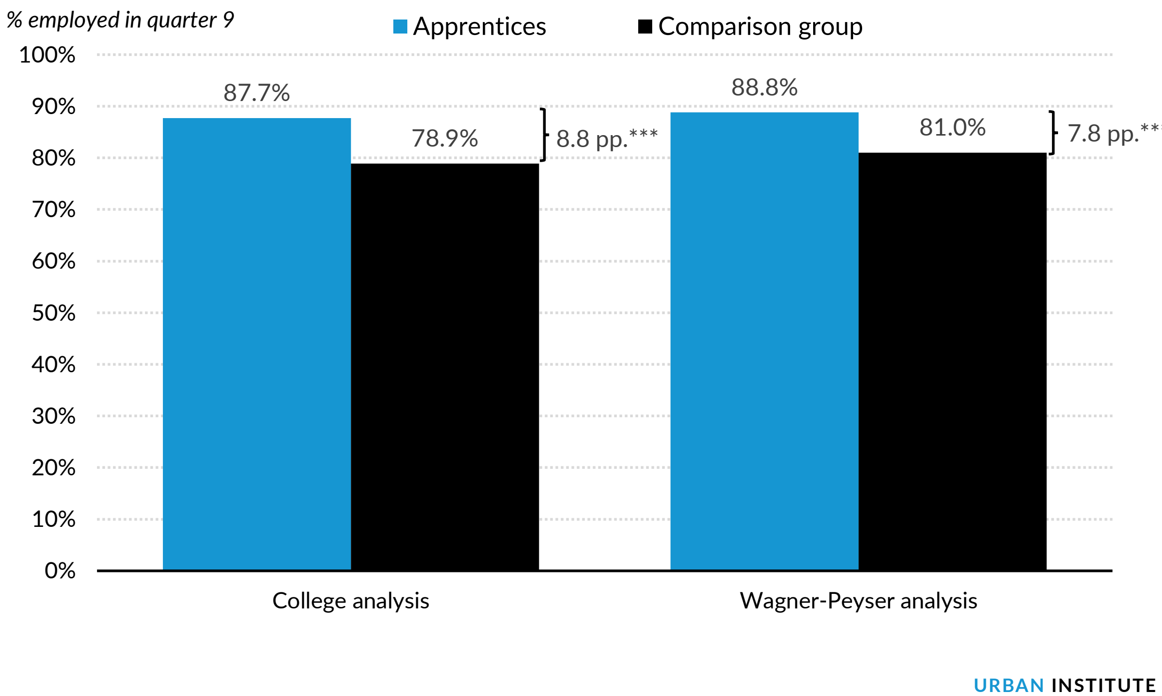
Key findings are presented separately for registered and unregistered apprenticeships. They are further broken down into two categories: one specific to the College analysis (i.e., the comparison group of community college students) and one for the Wagner-Peyser analysis (i.e., the comparison group of Wagner-Peyser participants).

- **Registered apprenticeship programs had large, statistically significant impacts on employment and earnings in the ninth quarter following enrollment relative to both comparison groups (primary research question).**

For registered apprentices, the positive impact of apprenticeship on employment in the ninth quarter following enrollment ranged from 7.8 percentage points (Wagner-Peyser analysis) to 8.8 percentage points (College analysis) (figure ES.1). Both were statistically significant at the 1 percent level. The relative impacts—that is, as a proportion of the comparison group mean—were approximately 10 percent and 11 percent for the Wagner-Peyser and College analyses, respectively (not shown).

FIGURE ES.1

Impact of Registered Apprenticeships on Employment Compared with Community College and Wagner-Peyser Participants



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

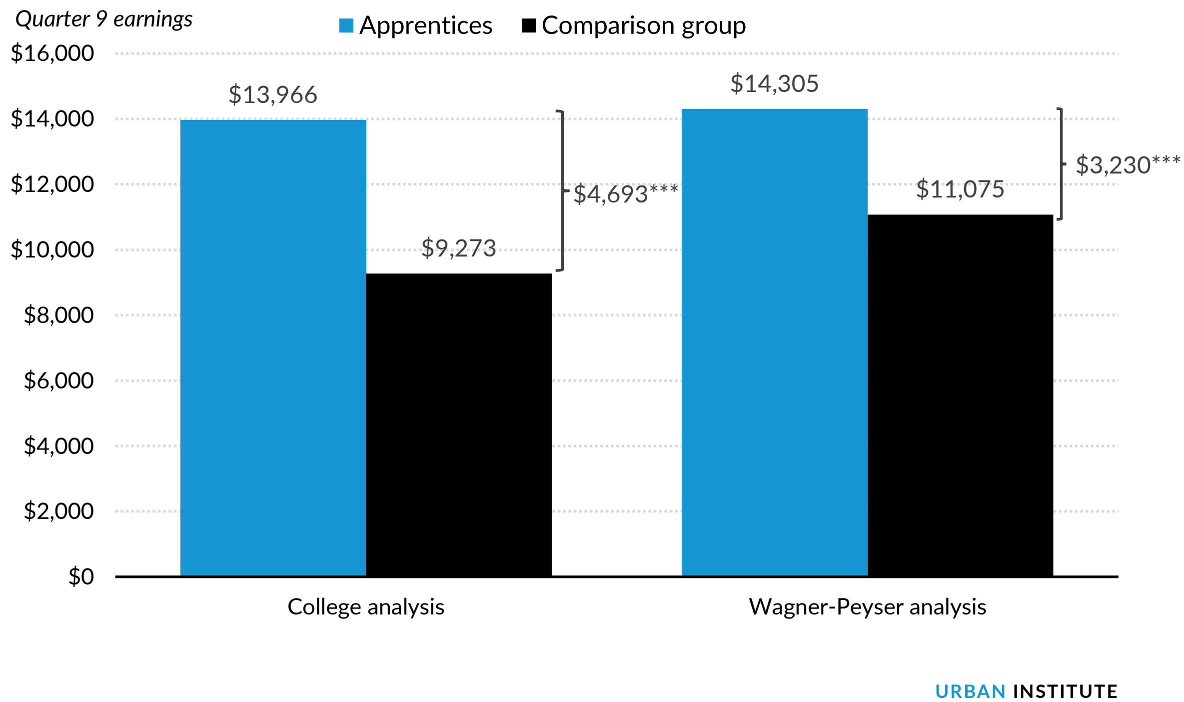
Notes: Employment is defined as having any earnings in the ninth quarter recorded in the National Directory of New Hires. Wagner-Peyser analysis: N=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N= 5,484 (1,124 apprentices and 4,360 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Registered apprenticeship's positive impact on ninth-quarter earnings ranged from $3,230 in the Wagner-Peyser analysis to $4,693 in the College analysis (figure ES.2). Both impacts were significant at the 1 percent level. The relative impacts were 29 percent and 51 percent, respectively.

FIGURE ES.2

Impact of Registered Apprenticeships on Earnings



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Wagner-Peyser analysis: N=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N= 5,484 (1,124 apprentices and 4,360 community college students).

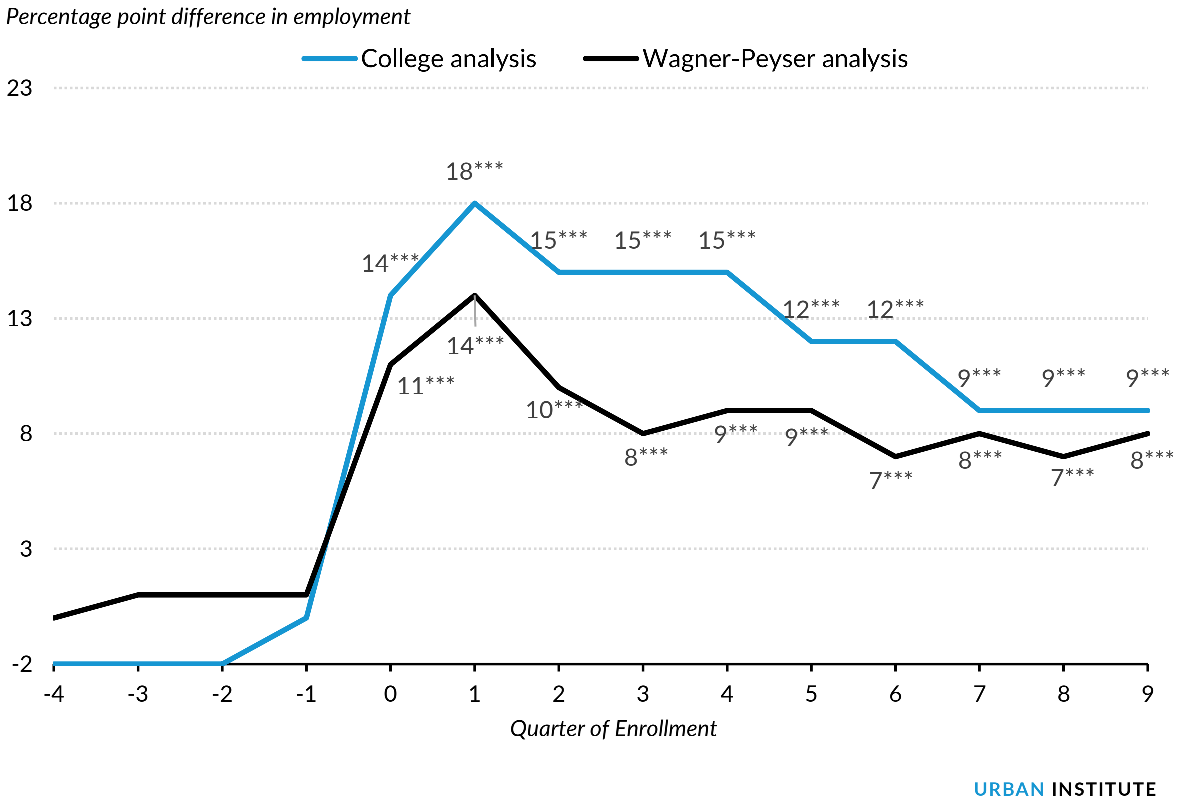
Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

- **Registered apprenticeship employment and earnings impacts began in Quarter 0 (the enrollment quarter) and continued through Quarter 9 post enrollment.**

Starting from the quarter when apprentices enrolled in their apprenticeships (Quarter 0), apprenticeships had positive, significant impacts on employment (figure ES.3). The largest impacts were in Quarter 1 (18 percentage points in the College analysis and 14 percentage points in the Wagner-Peyser analysis). The impacts were statistically significant at the 1 percent level from Quarters 0 through 9. There were no statistically significant differences in employment between the apprentices and their respective comparison groups during the four quarters prior to enrollment, as expected but not guaranteed by our matching design.

FIGURE ES.3

Impact of Registered Apprenticeships on Employment Over Time by Comparison Group



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

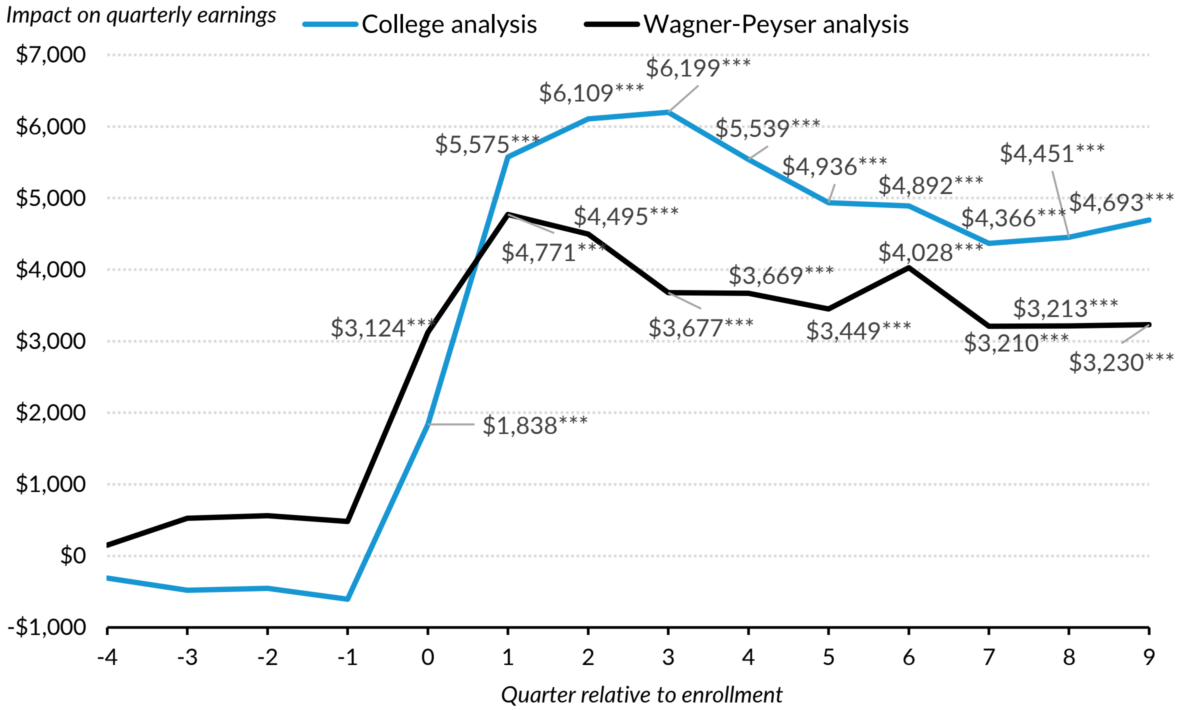
Notes: Each point in the figure is an impact estimate: the adjusted difference in earnings between apprentices and Wagner-Peyser participants or college students. Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter due to data availability. Wagner-Peyser analysis: N in ninth quarter=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N in ninth quarter= 5,484 (1,124 apprentices and 4,360 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Similarly, positive earnings impacts for both comparisons began in Quarter 0 and continued through Quarter 9 (figure ES.4). The quarterly earnings impact was largest in Quarter 1 in the Wagner-Peyser analysis ($4,771) and in Quarter 3 in the College analysis ($6,199). Earnings impacts were statistically significant in both comparison group analyses across all 10 quarters.

FIGURE ES.4

Impact of Registered Apprenticeships on Earnings Over Time



URBAN INSTITUTE

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Each point in the figure is an impact estimate: the adjusted difference in earnings between apprentices and Wagner-Peyser participants or college students. Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N in ninth quarter= 5,484 (1,124 apprentices and 4,360 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

- **Registered apprenticeship had strong ninth-quarter employment and earnings impacts for all occupations, relative to both comparison groups.**

Advanced manufacturing, IT, and health care registered apprenticeship programs had positive impacts on employment relative to both comparison groups (significant at the 1 percent level). Impacts ranged from 4.9 to 8.6 percentage points for advanced manufacturing, 6.0 to 12.2 percentage points for IT, and was 15.5 percentage points for health care.[3]

[3] Sample sizes were not large enough to estimate the impact on healthcare occupations for the Wagner-Peyser analysis.

The ninth-quarter earnings impacts followed a similar pattern. The earnings impacts ranged from $1,920 to $3,542 for advanced manufacturing, $3,120 to $3,862 for IT, and was $7,980 for health care (College analysis only due to sample size constraints). All impacts were statistically significant at the 1 percent level.

- **Registered apprenticeship had significant ninth-quarter employment and earnings impacts for most subgroups, relative to both comparison groups.**

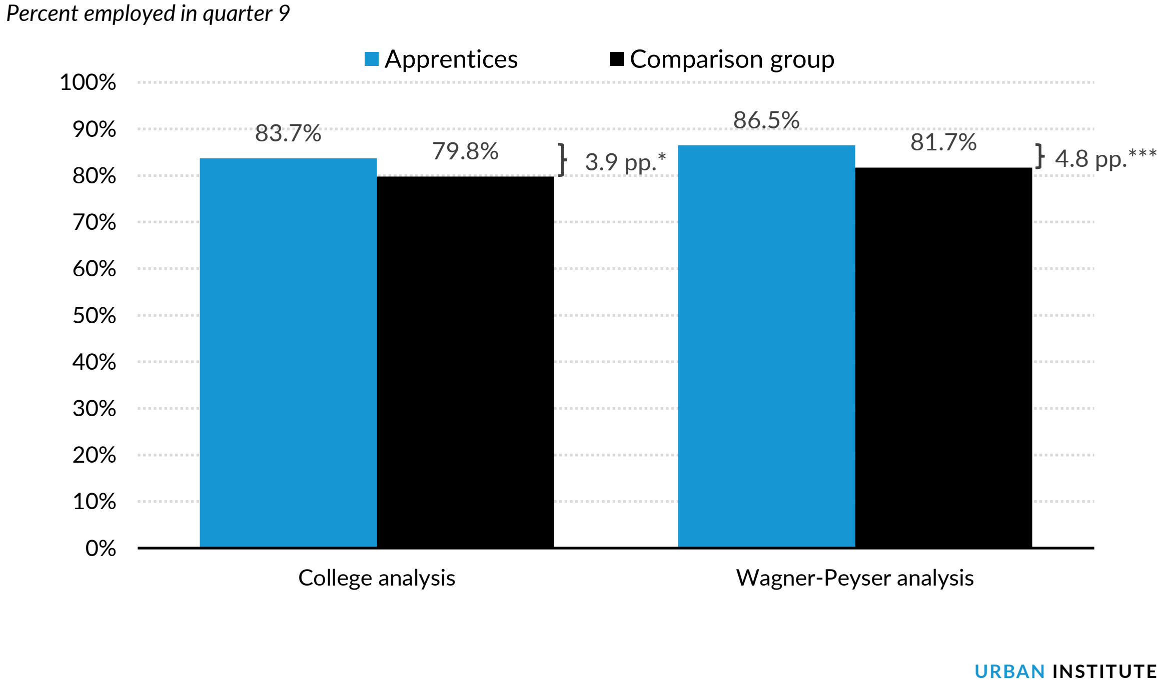
Registered apprenticeship had statistically significant impacts on employment for both incumbent and non-incumbent workers, for males, females, non-Hispanic whites, and non-Hispanic blacks. They were also generally significant for all age groups, except for those under age 25 in the Wagner-Peyser analysis. Employment impacts relative to both comparison groups were statistically significant at the 1 percent level. Registered apprenticeship also had large, statistically significant impacts on earnings for the same subgroups.

- **Unregistered apprenticeship programs had large, statistically significant impacts on ninth-quarter employment and earnings relative to both comparison groups (primary research question).**

The impact of unregistered apprenticeship on ninth quarter employment ranged from 3.9 percentage points to 4.8 percentage points (figure ES.5). Both were statistically significant at the 1 percent level. The relative impacts were 5 percent and 6 percent, respectively.

FIGURE ES.5

Impact of Unregistered Apprenticeships on Employment



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

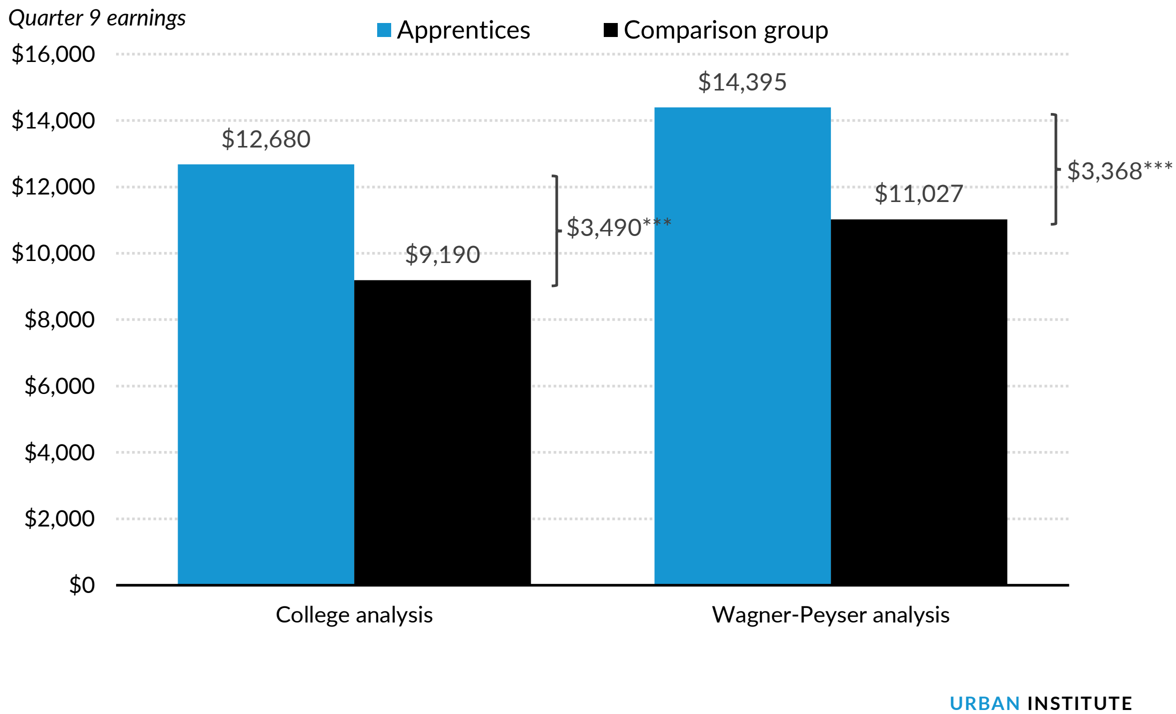
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Wagner-Peyser analysis: N=33,592 (950 apprentices and 32,642 Wagner-Peyser participants). College analysis: N= 3,670 (594 apprentices and 3,076 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Unregistered apprenticeship's impact on ninth-quarter earnings ranged from $3,368 to $3,490 (figure ES.6). Both impacts were significant at the 1 percent level. The relative impacts were 31 percent and 38 percent, respectively.

FIGURE ES.6

Impact of Unregistered Apprenticeships on Earnings



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Wagner-Peyser analysis: N=4,259 (315 apprentices and 3,944 Wagner-Peyser participants). College analysis: N= 3,670 (594 apprentices and 3,076 community college students).

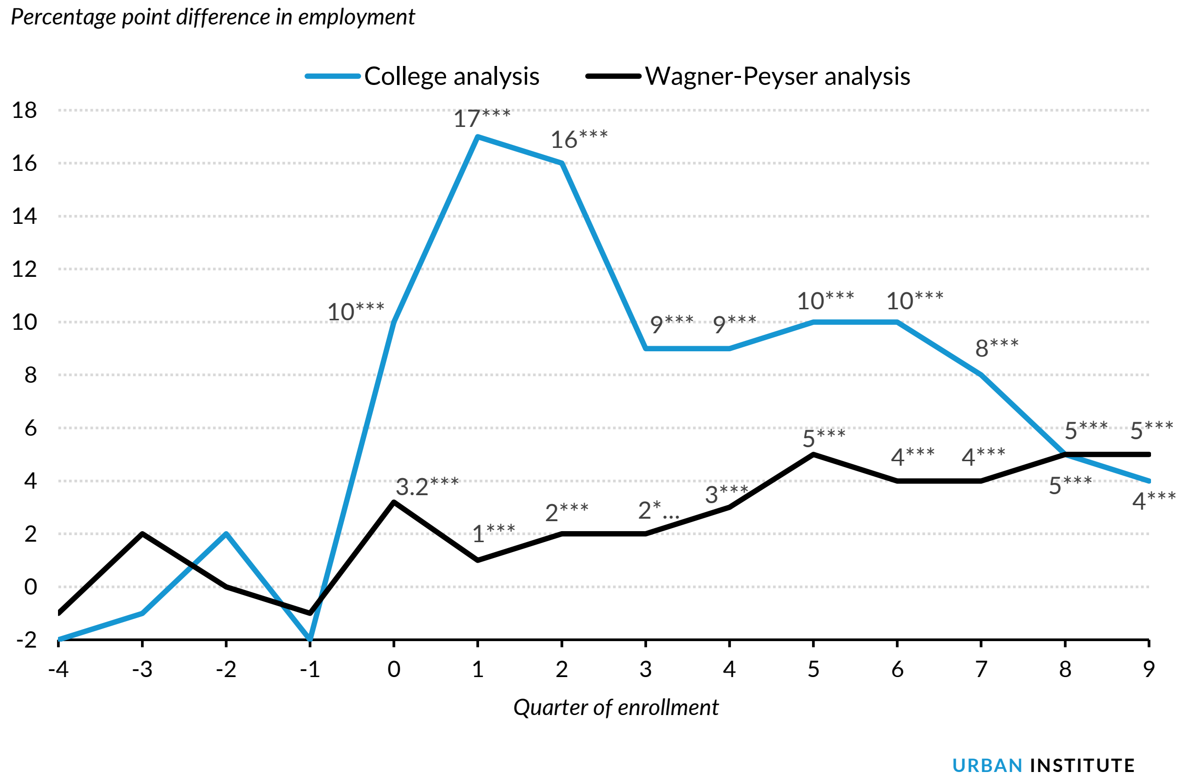
Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

- **Unregistered apprenticeship employment and earnings impacts began in Quarter 0 (the enrollment quarter) and continued through Quarter 9 post enrollment.**

Beginning Quarter 0, unregistered apprenticeship had strong, significant impacts on employment (9.5 percentage points in the College analysis and 3.2 percentage points in the Wagner-Peyser analysis, both statistically significant at the 1 percent level, figure ES.7). The largest impacts in the College analysis occurred in Quarter 1 (16.5 percentage points), likely representing the fact that many students in community college are not simultaneously employed. In the Wagner-Peyser analysis, in contrast, the impacts grew over time, peaking in Quarter 8 (5.1 percentage points). The impacts were statistically significant at the 1 percent level in Quarters 1 through 9. There were no statistically significant differences in employment between the apprentices and their respective comparison groups during the four quarters prior to enrollment.

FIGURE ES.7

Impact of Unregistered Apprenticeships on Employment Over Time



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

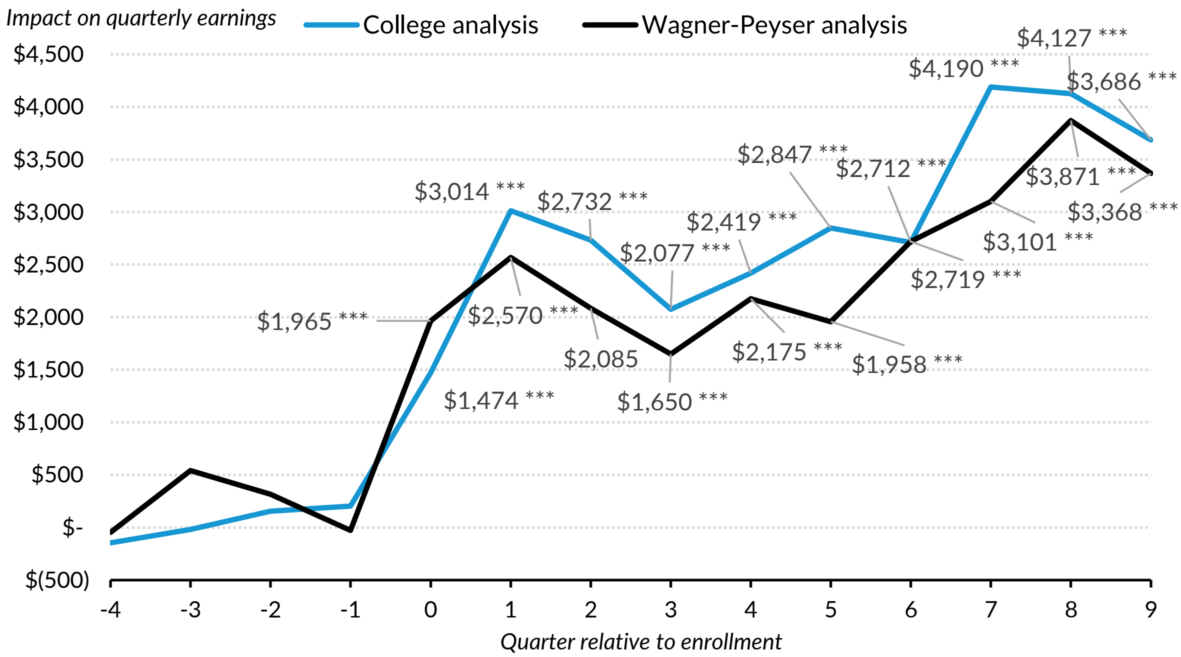
Notes: Each point in the figure is an impact estimate: the adjusted difference in earnings between apprentices and Wagner-Peyser participants or college students. Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=4,259 (315 apprentices and 3,944 Wagner-Peyser participants). College analysis: N=3,670 (594 apprentices and 3,076 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Similarly, earnings impacts began in Quarter 0 ($1,474 and $1,965 for the College and Wagner-Peyser analyses, respectively). The largest quarterly impacts were in Quarter 7 ($4,190 for the College analysis) and Quarter 8 ($3,871 for Wagner-Peyser analysis).

FIGURE ES.8

Impact of Unregistered Apprenticeships on Earnings Over Time



URBAN INSTITUTE

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.
Notes: Each point in the figure is an impact estimate: the adjusted difference in earnings between apprentices and Wagner-Peyser participants or college students. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=4,259 (315 apprentices and 3,944 Wagner-Peyser participants). College analysis: N in ninth quarter=3,670 (594 apprentices and 3,076 community college students).
Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

- **Unregistered apprenticeships had strong ninth-quarter employment and earnings impacts for advanced manufacturing.**

Unregistered apprenticeships had a strong impact on ninth-quarter employment for advanced manufacturing, ranging from 5.1 to 7.8 percentage points, depending on the comparison group (significant at the 1 percent level). These translate into relative impacts of 6 percent and 9 percent, respectively. (Sample sizes were not large enough to estimate impacts for other occupations).

Advanced manufacturing unregistered apprenticeships also had a strong, significant (at the 1 percent level) impact on ninth-quarter earnings, ranging from $3,121 to $3,686 depending on the comparison group (or relative impacts of 23 percent and 27 percent, respectively).

- **Unregistered apprenticeship had mixed ninth-quarter employment and earnings impacts for subgroups.**

Unregistered apprenticeships had significant ninth-quarter employment impacts relative to both comparison groups only for non-Hispanic whites (one of the comparisons was significant at only the 10 percent level). There were significant impacts at the 1 percent level for males, and the age groups 25-39 and 40 and older, but only in the Wagner-Peyser analysis. Unregistered apprenticeships did not have statistically significant ninth-quarter earnings impacts for incumbent workers relative to either comparison group, and the impact for non-incumbent workers was statistically significant in only the Wagner-Peyser analysis.

Conversely, unregistered apprenticeship had statistically significant impacts on ninth-quarter earnings in both comparison group analyses for males, non-Hispanic whites, non-Hispanic Blacks, those under age 25, and non-incumbent workers. Impacts for incumbent workers, and those ages 25-39 and 40 and older were significant at the 1 percent level only in the Wagner-Peyser analysis.

Implications for Apprenticeship Program Operators and Policymakers

The Scaling Apprenticeship and Closing the Skills Gap grantee impact study findings provide additional insight into the effectiveness of employer-based training programs—particularly apprenticeship. Based on these findings, we outline key implications for future apprenticeship programs and research below:

- **Both registered and unregistered programs can have positive impacts on employment and earnings.** Much of the literature focuses on the effectiveness of registered apprenticeship programs. This study showed that unregistered programs, as well as registered ones, can have strong employment and earnings impacts. It is noteworthy that the Funding Opportunity Announcements required all unregistered programs funded by Scaling Apprenticeship and Closing the Skills Gap grants to incorporate components commonly associated with registered apprenticeships, including paid, work-based learning, on-the-job training and mentorship, an educational or instructional component, and an industry-recognized credential upon completion.
- **Apprenticeships in nontraditional occupations can generate positive impacts.** Although primarily used as a training model in the construction sector, the impact study results show that apprenticeship is an effective model for training individuals in other occupational sectors

as well. Registered apprenticeship programs in advanced manufacturing, IT, and health care occupational sectors produced strong employment and earnings impacts, as did unregistered advanced manufacturing programs. The findings suggest that efforts to expand apprenticeship to non-traditional occupations can be successful.

- **Apprenticeship is an effective way to train workers in high-demand occupations**. The impact study findings show that registered and unregistered apprenticeship prepares workers for high-demand occupations—particularly those facing skill shortages. Although it might seem that the same challenges driving these shortages (such as rapidly changing skill requirements or limited training opportunities) would also make it difficult to train workers, the results suggest otherwise. They provide evidence that, with the right structure and employer involvement, apprenticeship can successfully prepare American workers to meet the demands of high-growth sectors.
- **Apprenticeship is effective for both incumbent and non-incumbent workers.** Registered and unregistered apprenticeships are effective for both helping existing workers attain higher positions with their current employers (incumbent workers) and for facilitating new opportunities for workers who are new to an employer (non-incumbent workers).
- **Positive impacts are not limited to any specific worker profile.** The study found significant employment and earnings impacts of registered and unregistered apprenticeship across sex, race/ethnicity, and age, although a number of subgroups could not be analyzed due to insufficient sample size. The size and statistical significance of the impacts differed by subgroup. However, the findings provide evidence that grantees and their partners were able to successfully expand apprenticeship opportunities to a broad range of Americans.

This impact study adds to the apprenticeship evidence base. Future studies could continue to explore employment and earnings impacts of registered and unregistered programs for a wider range of programs, including those not supported by federal funding and additional occupational areas.

The Impact of Registered and Unregistered Apprenticeship

Chapter 1: Introduction

Apprenticeship is an "earn and learn" employer-based training model that combines technical instruction in a physical or virtual classroom with learning and mentoring on the job. Apprentices are hired by their employers and earn progressively higher wages over the course of the apprenticeship. Long used as a training model for construction-related occupations, in 2015 the U.S. Department of Labor (DOL) began funding grant programs to expand apprenticeship to nontraditional occupations—those outside of construction—across a range of industries and occupations, and to all Americans.

This report presents findings from the impact study of two DOL grant programs: Scaling Apprenticeship through Sector-Based Strategies (Scaling Apprenticeship) and Apprenticeships: Closing the Skills Gap (Closing the Skills Gap). Between these two grant programs, DOL awarded almost $284 million to 51 grantees between 2019 and 2020. The DOL Chief Evaluation Office (CEO) commissioned an evaluation of these grantee programs as part of the Apprenticeship Evidence-Building Portfolio project, which seeks to document the design, implementation, and impacts of recent DOL investments in apprenticeship. The impact study assesses the effect of both grant programs on the employment and earnings of apprentices nine quarters after enrollment relative to non-participants in two matched comparison groups. The Urban Institute and its partner, Mathematica, conducted the impact evaluation.

This chapter first describes the goal of the grant programs and provides an overview of the grants. It then summarizes evidence from evaluations of similar programs. Next, it describes the impact study design. The chapter concludes with a roadmap to the remainder of the report.

Goals and Overview of Grant Programs

In their grant applications, the Scaling Apprenticeship and Closing the Skills Gap grantees identified the types of apprenticeship programs they intended to support, including their occupational focus. Grantees in both programs could create new registered or unregistered apprenticeship programs, or scale both types.[4] Registered programs, described in more detail below, are approved by either the DOL Office of Apprenticeship (OA) or a federally recognized state apprenticeship agency (SAA), while unregistered programs are not.

Both grant programs had similar goals: expanding apprenticeships in H-1B industries and occupations with high demand for skilled workers,[5] and increasing apprenticeship opportunities for all Americans. Both grants focused on occupations associated with three industries: advanced manufacturing, information technology (IT), and health care. Closing the Skills Gap grantees had an added goal of expanding apprenticeship in artificial intelligence- and cybersecurity-related occupations within the larger IT sector. Eligible participants were unemployed, underemployed, or incumbent workers (workers currently employed), 17 years of age or older, and not currently enrolled in school within a local educational agency.[6] Details of the grant programs are summarized below.

Scaling Apprenticeship Grants

In June 2019, DOL awarded $183.8 million in Scaling Apprenticeship grants to 23 grantees in 18 states. The grants had a 48-month period of performance, with a planning period of up to nine months before the start of enrollment. All grantees received no-cost extensions to continue their work beyond the original four-year grant period. The last grants closed in July 2024.

[4] The grants also initially supported Industry-Recognized Apprenticeship Programs (IRAPs), a DOL program where qualified third-party entities, known as Standards Recognition Entities, were authorized to oversee unregistered apprenticeship programs. In September 2022, DOL rescinded IRAPs to redirect resources to expanding registered apprenticeship. See "Apprenticeship Programs, Labor Standards for Registration," Federal Register, accessed July 29, 2025, https://www.federalregister.gov/documents/2022/09/26/2022-20560/apprenticeship-programs-labor-standards-for-registration. DOL OA traditionally capitalizes "Registered Apprenticeship Program," but we have chosen not to capitalize here to ensure uniformity between the terms "registered apprenticeship" and "unregistered apprenticeship." Although expansion of registered apprenticeship is an important policy goal for DOL, registered apprenticeship was not preferred or privileged under the Scaling Apprenticeship and Closing the Skills Gap grant programs.

[5] The H-1B visa program helps employers who cannot otherwise obtain needed business skills and abilities from the U.S. workforce by authorizing the temporary employment of qualified individuals who are not otherwise authorized to work in the United States. See "H-1B Program," U.S. Department of Labor, accessed June 16, 2025, https://www.dol.gov/agencies/whd/immigration/h1b.

[6] See "Notice of Availability of Funds and Funding Opportunity Announcement for: Scaling Apprenticeship Through Sector-Based Strategies," U.S. Department of Labor, accessed July 29, 2025, https://www.dol.gov/sites/dolgov/files/eta/grants/pdfs/foa-eta-18-08.pdf and "Notice of Availability of Funds and Funding Opportunity Announcement for: Apprenticeships: Closing the Skills Gap," U.S. Department of Labor, accessed July 29, 2025, https://www.dol.gov/sites/dolgov/files/ETA/skillstraining/FOA-ETA-19-09%20CSG.pdf.

Only institutions of higher education (IHEs), including community colleges, state higher education systems, or a consortium of higher education institutions could apply for Scaling Apprenticeship grants. These grants aimed to accelerate the expansion of apprenticeship as an effective and innovative postsecondary education and training pathway.[7] About half of the grantees were community or technical colleges, with the remainder evenly split between four-year universities and state college systems. Per grant applications, the most common target populations were unemployed individuals and workers currently employed (i.e., incumbent workers).

Grant amounts ranged from $2 million to $12 million. DOL expected grantees with the largest awards to serve 5,000 or more apprentices, while those with the smallest awards to serve a minimum of 800 apprentices. Grantees collaborated with industry associations to increase apprenticeship through two key activities: training apprentices and increasing the number of apprenticeship programs.[8] They could also use funds to support the design and implementation of pre-apprenticeship programs that served as on-ramps to apprenticeship opportunities, if the training was on a career pathway that led to middle- to high-skilled occupations.[9]

Closing the Skills Gap Grants

In February 2020, DOL awarded $99.3 million to 28 Closing the Skills Gap grantees in 22 states. (Three grantees ended early.) As with Scaling Apprenticeship grants, these grants had a 48-month period of performance and a 9-month planning period. About half of grantees received no-cost extensions to continue their work beyond the original four-year grant period. Most grants closed by February 2025.

Whereas all Scaling Apprenticeship grantees were affiliated with IHEs, Closing the Skills Gap grantees could be IHEs, nonprofit trade organizations, industry or employer associations, labor unions, or labor-management organizations. Over half of Closing the Skills Gap grantees were IHEs (most commonly four-year universities). The next most common grantee types were industry associations,

---

[7] IHE involvement in the apprenticeship system is growing. In 2016, only 30 community colleges sponsored registered apprenticeship programs. By 2023, over 200 community colleges trained over 15,500 apprentices (Lerman et al. 2024). This, however, still represents only 3 percent of all civilian apprentices, indicating the potential for further expansion of IHE involvement in apprenticeship.

[8] See "Notice of Availability of Funds and Funding Opportunity Announcement for: Scaling Apprenticeship Through Sector-Based Strategies, FOA-ETA-18-08," U.S. Department of Labor, accessed June 16, 2025, https://www.dol.gov/sites/dolgov/files/ETA/skillstraining/FOA-ETA-18-08%20Scaling%20Apprenticeship.pdf.

[9] Grant applicants could choose to expand apprenticeships in either an industry or occupations in which DOL certified H-1B visas. These H-1B occupations are considered high-skilled industries.

union-affiliated organizations, and workforce intermediaries. Per grant applications, the most cited grantee target populations were veterans and incumbent workers. Grantees could use funding for new or expanded registered or unregistered apprenticeships but not for pre-apprenticeships.[10]

Relative to Scaling Apprenticeship grants, Closing the Skills Gap awards were smaller; the largest grant amount was $6 million. As with Scaling Apprenticeship grantees, DOL expected Closing the Skills Gap grantees with the largest awards to serve 5,000 or more apprentices, while those with the smallest awards to serve a minimum of 800 apprentices.

Apprenticeship Programs Supported by Grants

The Funding Opportunity Announcements for both grant programs required all apprenticeship programs, whether registered or unregistered, to include the following elements:

- Paid, work-based learning at an employer site,
- On-the-job training (OJT) and mentorship (called "on the job learning" in apprenticeship regulations but OJT in the Funding Opportunity Announcements),
- Related technical instruction (RTI), an educational or instructional component (called "related instruction" in apprenticeship regulations but RTI in the Funding Opportunity Announcements),
- An industry-recognized credential upon completion, and
- Safety and supervision policies and procedures.

Although both registered and unregistered programs include these five elements, they also have key differences.

Registered apprenticeship programs must be approved by either OA or an SAA.[11] OA recommends that a registered apprenticeship program includes at least 144 hours per year of RTI and requires at least 2,000 hours of OJT. The 2,000-hour requirement means that registered programs are typically at least one year long, but they are often two to five years long, depending on the occupation. A program sponsor is responsible for the program and maintains the Standards of

[10] See "Notice of Availability of Funds and Funding Opportunity Announcement for: Apprenticeships: Closing the Skills Gaps, FOA-ETA-19-09, U.S. Department of Labor, accessed June 16, 2025, https://www.dol.gov/sites/dolgov/files/ETA/skillstraining/FOA-ETA-19-09%20CSG.pdf

[11] As of July 2024, 21 states registered programs with OA and 29 states plus Washington, DC, registered programs with an SAA.

Apprenticeship, which documents the RTI, OJT, wage structure, and other aspects of the program. Sponsors can be employers, a consortium of employers, unions, IHEs, state or local workforce agencies, or nonprofit organizations.[12]

Registration forms and the Standards of Apprenticeship[13] submitted for registration approval describe:

- the responsibilities of the sponsor;
- the minimal qualifications of apprentices (e.g., age, education);
- apprenticeship program type and length;
- a work process schedule that outlines the major job functions and what apprentices are expected to learn on the job, and a related instruction outline;
- the ratio of apprentices to mentors;
- the apprentice wage schedule;
- selection procedures; and
- the apprentice probationary period.

Unregistered apprenticeship programs are not reviewed or approved by OA or an SAA. Program duration can vary by occupation. Unregistered apprenticeships can be shorter than registered apprenticeships because they do not have to meet the same requirements for the number of RTI and OJT hours. Because they are not registered with OA or a federally recognized SAA, grantees can potentially implement or adapt programs more quickly. As noted above, all unregistered apprenticeship programs supported by the Scaling Apprenticeship and Closing the Skills Gap grants must include the five key components described above.

Participants and Apprentices

When applying for grants and subsequently reporting activities to DOL, grantees distinguished between the number of participants and apprentices served. Both grant programs defined *participation*

[12] See CFR Code of Federal Regulations Part 29, Section 29, accessed June 16, 2025, https://www.ecfr.gov/current/title-29/subtitle-A/part-29?.

[13] See "Modifications to the Boilerplate Standards of Apprenticeship," U.S. Department of Labor, accessed June 16, 2025, https://www.dol.gov/sites/dolgov/files/ETA/apprenticeship/pdfs/Bulletin%202022-17%20Modifications%20to%20the%20Boilerplate%20Standards%20of%20Apprenticeship.docx.

as receiving a grant-funded service, which includes enrollment in an apprenticeship program, enrollment in a pre-apprenticeship program (Scaling Apprenticeship grantees only), and assessments to determine skill levels, aptitudes, abilities, and competencies of participants. Many grantees in both programs proposed to serve 5,000 or more participants.

Apprentices are hired by an employer into an apprenticeship program, and some apprentices worked for the apprenticeship employer prior to moving into the apprenticeship program (known as "incumbent workers").[14,15] Although all apprentices are participants, some participants served with grant funds did not become apprentices. Per their grant applications, IHE grantees in both grant programs expected a smaller proportion of participants to transition to apprenticeship (77 percent, on average) relative to non-IHE Closing the Skills Gap grantees (99 percent, on average) (Gardiner et al. forthcoming).[16] Thus, Closing the Skills Gap grantees, on average, expected a higher share of participants to become apprentices than did Scaling Apprenticeship grantees.

Many of the grant-supported apprenticeship programs, both registered and unregistered, were specifically for incumbent workers. Incumbent worker apprentices worked for the sponsoring employer prior to starting the apprenticeship, and participate in the apprenticeship to move into a higher position or occupation for their same employer. Since they are not only employed prior to starting the apprenticeship, but in fact employed with the same employer that they work for as apprentices, they are different than many populations for which workforce and training services are typically designed.

[14] Each grant at the beginning of their program set a target number of individuals they would serve and reported quarterly on their progress. Scaling Apprenticeship grantees set goals for the number of "apprentices enrolled," while Closing the Skills Gap grantees set goals for the number of "participants employed." Although the two grant programs used different language, both categories of participants met the same apprenticeship requirements and DOL counted them as apprentices. For the purposes of comparing outcomes across grant programs, we identify both groups as apprentices.

[15] In theory, an apprentice could exit their apprenticeship program before starting their RTI, but they cannot be considered an apprentice until they have been hired by an employer.

[16] A companion study (Ruggiero and Payne) found that a sample of IHE grantees interviewed for the implementation study site visits found that participants commonly took pre-apprenticeship training (Scaling Apprenticeship grantees only) or the related instruction portion of the apprenticeship before employers hired them. Through exposure to training or other services at the IHE, participants might determine in advance of an apprenticeship that it is not the right pathway and opt for another option at the IHE or seek employment on their own.

COVID-19 and the Implementation of Grant Activities

The pandemic-related shutdowns in March 2020 occurred just weeks after DOL awarded the Closing the Skills Gap grants. During virtual site visits to 18 grantees (nine from each grant program), Closing the Skills Gap grantees described the implementation delays caused by the closing of colleges and employer sites.[17] Although DOL awarded the Scaling Apprenticeship grants in 2019, Scaling Apprenticeship grantees also described COVID-related disruptions to grant activities. Although they had begun recruiting apprentices before the pandemic, Scaling Apprenticeship grantees reported having to adjust their activities in response to the pandemic. Grantees in both programs noted that the pandemic exacerbated challenges to recruiting enough employers to ensure adequate apprenticeship spots for all interested participants.

Conversations with grantees indicated that implementation challenges related to COVID-19 varied by program occupation. Health care employers faced restrictions on activities in health care facilities, thus affecting OJT. In contrast, IT employers found it more feasible to provide RTI and OJT virtually. Advanced manufacturing employers' experiences were industry specific, but these employers often found it more difficult to train apprentices virtually. The sample of individuals used in the impact study started apprenticeship programs in the third quarter of 2021 or later, after the most severe period of the pandemic had ended. Still, it is possible that the programs, and impacts of the programs, could have been different without COVID-19.

Evidence from Prior Studies

The labor market effects of both registered and unregistered apprenticeship have been studied using quasi-experimental methods, but this evidence base has important gaps and weaknesses, such as the lack of studies focused on unregistered apprenticeship and apprenticeships in non-traditional occupations. This impact study was designed to address many of these gaps to strengthen the evidence base on apprenticeship.

Registered Apprenticeship

Prior research consistently finds that registered apprenticeship training raises the earnings and employment of participants. Reed et al. (2012) estimated that apprenticeships increased annual

[17] The 18 grantees were selected as part of the Scaling Apprenticeship and Closing the Skills Gap grant program implementation study. See Gardiner et al. (forthcoming).

earnings by $6,595 in the sixth year after enrollment and by $5,839 in the ninth year. In 2024 dollars, these annual impacts equal a $2,624 increase in quarterly earnings six years after enrollment, and a $2,182 increase in quarterly earnings nine years after enrollment.[18] These estimates reflect the experiences of registered apprentices in ten states. Hollenbeck and Huang (2003; 2006; 2016) conducted a series of studies on workforce development programs in Washington State and found that registered apprenticeship increased participants' quarterly earnings by $3,715 ($5,012 in 2024 dollars). Dula (2021) estimated even larger quarterly impacts for Washington State registered apprentices of $5,741 (or $7,024 in 2024 dollars).

Since Reed et al. (2012), Hollenbeck and Huang (2003; 2008; 2016), and Dula (2021) all analyzed the impact of statewide registered apprenticeship systems, many of the apprentices in their studies participated in traditional four-year registered apprenticeship programs in construction. Traditional construction apprenticeships are the backbone of the American apprenticeship system, and it is critical to understand how they impact workers, but their experiences may not be generalizable to emerging registered apprenticeship programs in health care, IT, and advanced manufacturing.

The most comprehensive mixed-methods study of registered apprenticeship in nontraditional fields such as health care, IT, and advanced manufacturing is the evaluation of the American Apprenticeship Initiative (AAI) grantees sponsored by DOL. The AAI evaluation included 46 grantees, most of which were community colleges, but it did not include a rigorous causal impact study. To make up for the lack of a true causal study, Katz et al. (2022) compared the earnings growth of AAI apprentices to the earnings of similar workers in the Census Bureau's Quarterly Workforce Indicators (QWI) data. They found that AAI apprentices earned $1,226 more in quarterly earnings in the tenth quarter after enrollment ($1,479 in 2024 dollars). One reason this estimate may be lower than those in earlier studies is that the QWI comparison group only included workers, whereas comparison groups in causal impact studies often include both employed and unemployed people. Katz et al. (2022) therefore provides an informative benchmark for comparison, but does not completely fill the evidence gap on registered apprentices in nontraditional fields.

Unregistered Apprenticeship

Much less is known about the effectiveness of unregistered apprenticeship than registered apprenticeship (Kuehn and Lerman 2021). The only causal impact study of an unregistered

---

[18] Reed et al. (2012) report that six-year impacts are from 2006 and nine-year impacts are from 2009. These are adjusted using the January 2006 and January 2009 consumer price index, respectively, and the December 2024 consumer price index.

apprenticeship program is by Jacoby and Haskins (2020), who used a matched comparison design (similar to this study) to compare the earnings of apprentices who completed the unregistered Kentucky FAME program to community college completers. They found that the unregistered apprenticeship completers earned $22,075 more in annual wages, or $5,519 in quarterly earnings ($6,752 in 2024 dollars).[19]

The Kentucky FAME study has several limitations. First, the study relied on a relatively small sample size (134 unregistered apprentices). So, although the results are statistically different from zero, they are imprecisely estimated. Further, by only looking at Kentucky FAME completers, the authors cannot speak to the experiences of apprentices who do not complete their training. Like the registered apprenticeship studies discussed above, the findings from Jacoby and Haskins (2020) are also difficult to generalize to other unregistered apprenticeship programs, because they only analyzed Kentucky FAME, a well-established unregistered apprenticeship program in a single field (manufacturing technicians).

Impact Study Design

The purpose of this study is to estimate the impact of the Scaling Apprenticeship and Closing the Skills Gap apprenticeship programs on earnings and employment. To do this, the evaluation team used a quasi-experimental design (QED).

Research Questions

The research questions focus on the difference between the average outcomes of the apprentices and the average outcomes individuals would have achieved if the Scaling Apprenticeship and Closing the Skills Gap programs did not exist (also referred to as the average treatment effect on the treated).

The **primary impact study research questions** are:

- What is the impact of registered apprenticeships on earnings and employment of participants in the ninth quarter following program enrollment?
- What is the impact of unregistered apprenticeships on earnings and employment of participants in the ninth quarter following program enrollment?

---

[19] These estimates come from Appendix table 2 in Jacoby and Haskins (2020). Jacoby and Haskins (2020) report median wages as their primary results without testing for statistical significance, but the mean wage differences in the appendix are more comparable to those in other apprenticeship impact studies.

The **secondary research questions** are:

- What are the impacts of registered and unregistered apprenticeships on ninth-quarter earnings and employment for different occupational sectors?
- What are the impacts of registered and unregistered apprenticeships on ninth-quarter earnings and employment for subgroups (sex, race/ethnicity, age, and incumbent worker status)?

The team selected the ninth quarter from program enrollment in the design phase of the study because many apprenticeship programs are two years or less and because, based on constraints imposed by the project timeline and the timing of data collection activities, it struck the best balance between being the longest duration (furthest in time from program enrollment) while providing a sufficiently large sample size for analysis.

Methods

The QED estimates causal impacts by comparing outcomes for apprenticeship participants with those of a matched comparison group of non-apprentices. Specifically, the evaluation team created two comparison groups that represent common workforce development pathways: (1) individuals who enrolled at a community college and trained in apprenticeship industries, and (2) individuals who received Wagner-Peyser Employment Services. For each group, we used inverse probability weighting to create a comparison group that most closely reflects the characteristics of apprentices in our sample. Using and comparing two distinct comparison groups provide a more robust understanding of how apprenticeship outcomes compare to those of alternative pathways.

The impact study methods rely on a "selection on observables" assumption. Simply put, this assumption is based on the idea that observable characteristics can account for any key factors that relate to both enrolling in an apprenticeship program, and employment and earnings outcomes (see Imbens 2004 for a review of this methodology). Although this assumption can never be fully tested, the design adheres to the following principles, found in the literature, for generating credible comparison groups when studying workforce development programs using QEDs (Heckman et al. 1998; Heckman, Ichimura, and Todd 1997; Glazerman, Levy, and Meyers 2003):

1. Selecting treatment and comparison groups from the same local areas so that they face the same local labor markets and service environments;

2. Using a rich set of socio-demographic variables from a common data source for both samples;[20] and,
3. Using preprogram earnings histories, in temporal periods no longer than a quarter, to capture pre-enrollment differences in employment and earnings that can influence later employment outcomes.

Data Sources

The impact evaluation relies on three main data sources described below. Each dataset, and the methods for linking the data, are described in more detail in the Technical Appendix.

- **Workforce Integrated Performance System (WIPS)**.[21] These data include individual-level information about Scaling Apprenticeship and Closing the Skills Gap participants, as well as the Wagner-Peyser comparison group. Grantees report data on apprentices and local American Job Centers (AJCs) report data on Wagner-Peyser participants, with the fields and definitions created by DOL. Among other variables, the data contain demographic characteristics, employment status at program entry, highest education level completed at program entry, ex-offender status, low-income status, basic skills level, and program entry and exit dates.
- **Community College Data**. Community college data, from community college systems or state departments of education, provide information on the community college comparison group and include the same demographic characteristics as the WIPS data. Community college data also contain information on students' enrollment and course history, which is helpful for narrowing the comparison group to students in fields that are similar to the apprentices' occupations.
- **National Directory of New Hires (NDNH)**. The NDNH data serve as a legally mandated national repository of quarterly employment, unemployment insurance, and quarterly wage data. These data are collected from state unemployment insurance agencies and federal employment records, and capture most wage and salary employment in the United States. We use the NDNH data to measure the employment and earnings of apprentices and comparison

[20] As described in the next section, the Wagner-Peyser contrast meets this condition. For the community college comparison contrast the data source for pre-program earnings and employment are the same across treatment and comparison groups, but the data source for socio-demographic variables differs.

[21] WIPS is the performance management system for the Workforce Innovation and Opportunity Act, and for other DOL-funded workforce programs. Data are entered and updated quarterly for participants.

group members, beginning in the fourth quarter prior to program enrollment and continuing through the ninth quarter following program enrollment.

Overview of the Report

The remainder of this report presents the findings from the impact evaluation of the Scaling and Closing grants. It is organized as follows:

- Chapter 2: Implementation of the grants and participant outcomes
- Chapter 3: Overview of the study approach and grantee selection
- Chapter 4: Selection of comparison groups and matching process
- Chapter 5: Impacts on earnings and employment
- Chapter 6: Conclusion and discussion
- Technical Appendix

Chapter 2: Implementation of Grants and Participant Outcomes

This chapter first summarizes findings from the implementation study of the Scaling Apprenticeship and Closing the Skills Gap grant programs, conducted as part of the larger study of these grant programs (Gardiner et al, forthcoming). It then discusses the implications of the implementation study findings for the impact study.

Key Findings from the Implementation Study

The implementation study documented variation in grantee apprenticeship program models, participant and apprentice recruitment strategies, participant and apprentice characteristics, services provided to and received by participants and apprentices, and differences among programs by grant program and program registration status. This section summarizes each topic.

Apprenticeship Models

As of March 31, 2024, grantees from both grant programs collectively created 3,318 new apprenticeship programs (62 percent of the total number of apprenticeship programs supported by the grants) and expanded 2,033 existing apprenticeship programs (38 percent of the total).[22] More grantees offered registered programs (45 grantees) than unregistered ones (31 grantees). Twenty-eight grantees supported both registered and unregistered programs.

Virtual site visits to 18 grantees provided additional information about 62 apprenticeship programs implemented by these grantees. The most common apprenticeship **occupations** were IT, advanced manufacturing, construction, and health care. Programs in computer and mathematical occupations (which include IT) accounted for 31 percent of programs, followed by occupations in production, installation, maintenance, and repair occupations (including advanced manufacturing) (26 percent of programs), construction (19 percent), and health care (18 percent). Six percent of programs were in other occupational areas.

[22] The number of new and expanded apprenticeship programs come from Scaling Apprenticeship and Closing the Skills Gap quarterly progress reports as of March 31, 2024.

Program design varied by occupation. For example, 68 percent of apprenticeships in IT (computer and mathematical occupations) were expanded, followed by 63 percent of advanced manufacturing programs (production, installation, maintenance, and repair occupations). In contrast, nearly 73 percent of programs in health care were newly developed as a part of the grants. The **duration of programs** also differed by occupation. Advanced manufacturing programs averaged 3,750 hours, whereas IT and health care programs were shorter on average (2,807 hours and 2,000 hours, respectively).

Colleges provided **RTI** for 71 percent of the apprenticeship programs included in the site visits, while employers provided RTI for another 26 percent.[23] Colleges provided RTI for 89 percent of advanced manufacturing occupations and 83 percent of construction occupations. IT and health care occupations used a mix of colleges (42 percent and 55 percent, respectively) and employers (47 percent and 45 percent, respectively) for RTI.

Recruitment

Site visit grantees reported using multiple recruitment strategies to identify and enroll participants and apprentices. No grantees relied entirely on their own staff for recruitment; rather, they engaged a variety of partners to help them. The type of partners differed somewhat by whether the grantee was an IHE (12 grantees) or not (6 grantees). The most reported recruitment partners were employers (67 percent of IHE and non-IHE grantees), which is not surprising given the central role of employers in apprenticeship programs and the focus of some grantees on recruiting incumbent workers. Half of IHE grantees cited AJCs as a partner, as did 42 percent of non-IHE grantees. A larger share of IHE grantees reported colleges as a recruitment partner, while a greater proportion of non-IHE grantees partnered with high schools and pre-apprenticeship programs.

Partners used different recruitment strategies. Employers participated in recruitment events at colleges alongside instructors and hosted apprenticeship launch events. College partners reported recruiting students from their non-degree and experiential learning programs. Other IHE grantees used statewide community college systems to market apprenticeship widely.

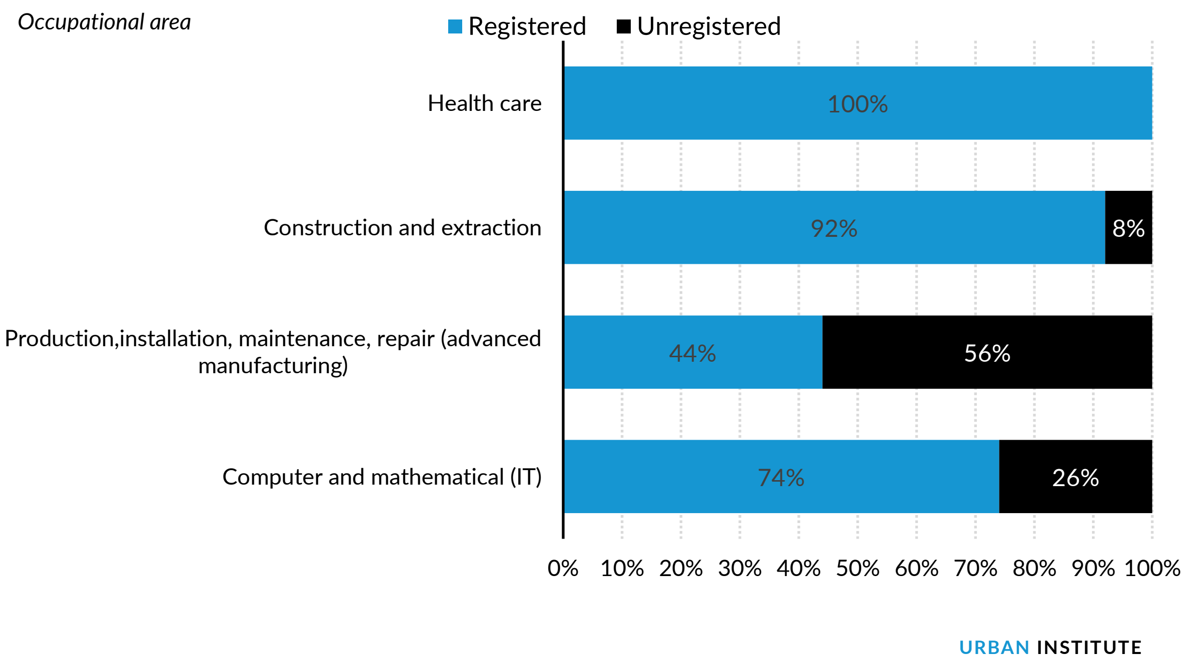
[23]Colleges provided the training for most programs in production/installation/maintenance/repair, construction and extraction, and healthcare. Employers provided training for slightly more computer and mathematical programs than did colleges (47 percent versus 42 percent).

Key Distinctions Between Registered and Unregistered Programs

Among site visit grantees, the proportion of registered versus unregistered programs varied by occupation (figure 2.1). All health care apprenticeship programs were registered, as were 92 percent of construction programs, and 74 percent of computer/mathematical (e.g., IT) programs. Conversely, the majority of production/installation/maintenance/repair (e.g., advanced manufacturing) programs were unregistered (56 percent).

FIGURE 2.1

Apprenticeship Program Type by Occupation



Source: Site visits with Closing the Skills Gap and Scaling Apprenticeship grantees and partners conducted between the fall of 2022 and the spring of 2023. N=62 programs.

Registered and unregistered programs also differed in whether they were new or expanded, and in their approach to measuring skill development. A smaller proportion of registered programs were expanded rather than new (56 percent), compared with 65 percent of unregistered programs.

Considerations for the Impact Study

The implementation study documented notable variations in program implementation that are relevant for the impact analysis:

- **Implementation differed between registered and unregistered programs**. A larger share of the unregistered apprenticeship programs was expanded rather than newly created using grant funds, which may indicate that they were operational and ready to hire apprentices sooner than the registered programs. The distribution of registered and unregistered programs also varied by occupation with advanced manufacturing being the only occupation where most programs were unregistered. Additionally, apprentices in registered and unregistered programs varied by some demographic (e.g., sex) and educational (e.g., attainment) characteristics. Moreover, unregistered apprenticeship programs were shorter on average than registered programs (2,908 hours compared with 3,489), but the difference was not statistically significant. This suggests that while the unregistered apprenticeship programs supported by grantees may be less intensive on average than the registered apprenticeship programs, the difference is not substantial. These average program durations and times to completion also indicate that earnings and employment impacts at nine quarters post-enrollment should reflect earnings and employment after expected completion for most apprentices.
- **Implementation differed between occupations.** In addition to differences in registration status, occupations differed in program length, methods for assessing skills gains, and participant characteristics.

The impact study addresses these considerations in the following ways:

- Registered and unregistered apprenticeship program impacts are reported separately in Chapter 5.
- Impacts are presented by occupation and participant characteristics in Chapter 5.

Chapter 3: Study Design and Treatment Group Selection

This quasi-experimental impact study generates estimates of the effects of participating in registered and unregistered apprenticeship programs under the Scaling Apprenticeship and Closing the Skills Gap grant programs on apprentice earnings and employment.[24] The evaluation team estimated the impact of participation in an apprenticeship on ninth quarter post-enrollment employment and earnings relative to two separate comparison groups: individuals who receive limited employment services from the Wagner-Peyser program and individuals attending community college. These comparison groups, after being statistically weighted to align with the grant-supported apprentices, are used as "counterfactuals" for apprentices, or an approximation of what individuals would have experienced had they not enrolled in the apprenticeship program. These two alternatives each represent a pathway that individuals use to improve their labor market outcomes and are thus a relevant comparison for apprentices seeking similar improvements in their outcomes. The team selected the ninth quarter from program enrollment because many apprenticeship programs are two years or less and because it struck the best balance between the longest duration (furthest in time from program enrollment) while providing a sufficiently large sample size for analysis.

The remainder of this chapter describes selection of registered and unregistered apprentices in the analysis samples. First, it discusses our process for selecting Scaling Apprenticeship and Closing the Skills Gap grantees to pursue for the impact study. Next, it briefly describes the requirements for an apprentice to be included in the analysis sample. It then presents the characteristics of the grantees that were included in the impact analysis. Finally, it compares the impact sample of apprentices to the broader universe of apprentices served by the Scaling Apprenticeship and Closing the Skills Gap grantees. Additional details on study design, data sources, and analyses are provided in subsequent sections and the Technical Appendix.

[24] The evaluation team explored conducting a randomized controlled trial (RCT). However, based on multiple conversations with a broad set of grantees, the team determined, in collaboration with DOL, that an RCT was not feasible. The evaluation team learned that grantees did not plan to have substantially more eligible applicants than they could serve (so random assignment would limit the number of apprentices they would be able to serve unless they scaled up recruitment efforts), and that grantees partner closely with employers that wish to choose their own apprentices, which presents a critical challenge to random assignment. Challenges implementing an RCT to study apprenticeship training are described in more detail in Kuehn and Macklin (forthcoming).

States and Grantees Selected

The quasi-experimental design for this study relied on collecting personally identifiable information (PII) on all individuals in the treatment and comparison groups, including Social Security numbers (SSNs). Although the SSNs were available to the study team for apprentices, we needed to develop partnerships with state workforce agencies and educational institutions to provide data on the comparison groups. As a result, the sample for this study was dictated by the states and educational institutions with which we were able to develop data use agreements. If a state or educational institution agreed to share PII, the analyses included apprentices within that state. Many grantees operated across multiple states, such that a given grantee might have some of its apprentices included in the impact study sample and not others.

Selecting States

To identify target states for developing data sharing agreements, the evaluation team first aggregated grantee-level information on apprentice targets to the state level based on each grantee's reported service area. For grantees operating in multiple states, the team assumed apprentices would be equally distributed across those states.[25] The team then generated possible combinations of states and scored each according to the following selection criteria: expected number of apprentices, expected number of grantees, minimal deviation from the overall occupational distribution of apprentices, and minimal deviation from the overall geographic distribution of apprentices. Because the study aimed to estimate impacts for registered and unregistered apprenticeship, separately, we selected sets of states for each type separately, though there was significant overlap in the highest scoring states for registered and unregistered apprenticeships.

After selecting a set of target states, we approached the target states' workforce agencies to establish data use agreements for accessing data. The team was successful in entering into data use agreements for Wagner-Peyser data with nine state workforce agencies: Alabama, Connecticut, Florida, Indiana, Michigan, Missouri, New Jersey, Pennsylvania, and Utah.[26] For community college data, we approached the community college system or state department of higher education, depending on which entity held the individual-level data with PII we needed. When those entities were unable to share data, we approached individual community colleges within these states,

[25] Grantees that operate across states did not report the target number of apprentices by state.

[26] We had originally made a data use agreement with Arkansas but due to data quality concerns, we dropped Arkansas from the analysis.

including colleges that were themselves grantees; although the college departments that we worked with were distinct from those that oversaw the grants. (That is, a given community college might also be a grantee; for the purpose of the study design, they serve both roles). The team entered into data use agreements for community college data with entities in eight states: Alabama, California, Illinois (Illinois Community College Board), Indiana (Ivy Tech Community College), Missouri, New Jersey (NJ Office of the Secretary of Higher Education), Ohio (Ohio Department of Higher Education), and Texas (Dallas College and San Jacinto College). In total, 13 of the 29 states with Scaling Apprenticeship and Closing the Skills Gap grant recipients provided data—exceeding the 10 states included in Reed et al.'s 2012 impact study.

Selected States' Grantee Characteristics

The impact study states in the analyses included 22 grantees: 14 Scaling Apprenticeship grantees and 8 Closing the Skills Gap grantees. Table 3.1 shows the grantees, their focus occupation(s), and the proportion of apprentices in registered programs. To be included in the impact study, apprentices had to meet certain conditions, described in the next section.

The impact study grantees' target occupations were similar to those of all grantees. Forty-seven percent of impact study grantees focused on IT, either as the sole occupation or one of two, compared with 44 percent of all grantees. The next most common occupation was advanced manufacturing (33 percent of impact study grantees versus 36 percent of all grantees). The least common occupation was health care (20 percent of grantees in each group).

The number of apprentices that grantees enrolled by March 31, 2024, ranged from 148 to 7,255. The median impact study grantee enrolled 2,159 apprentices. Impact study grantees varied in the percentage of apprentices in registered programs. Thirteen of the 22 grantees enrolled more than 50 percent of their apprentices in registered programs versus nine that enrolled 50 percent or fewer apprentices.

TABLE 3.1

Characteristics of Grantees Included in Impact Study

Grantee	Focus Occupation(s)	Number of Apprentices Enrolled	Percent of All Apprentices in Registered Programs
Scaling Apprenticeship Grantees			
Alabama Community College System	Advanced Manufacturing	1,600	9
Bergen Community College	Health care	862	100
Columbus State Community College	Information Technology	458	1
County College of Morris	Advanced Manufacturing	399	100
Dallas County Community College District	Health care	6,658	98
Illinois Community College Board	Information Technology	1,313	20
Lorain County Community College	Advanced Manufacturing	2,962	36
Pennsylvania College of Technology	Advanced Manufacturing	2,014	66
San Jacinto Community College District	Information Technology	2,303	52
St. Louis Community College	Advanced Manufacturing	2,547	32
Trustees of Clark University	Information Technology	1,333	100
University of Cincinnati	Information Technology	7,255	0
Weber State University	Information Technology	475	100
West Los Angeles College	Advanced Manufacturing	5,363	44
Closing the Skills Gap Grantees			
American Association of Port Authorities	Information Technology, Advanced Manufacturing	2,917	73
Florida Alcohol and Drug Abuse Association	Health care	148	100
Goodwin College, Inc.	Advanced Manufacturing	1,098	5
Ivy Tech Community College of Indiana	Information Technology	3,517	53
Missouri Chamber Foundation	Information Technology	3,342	100
North Carolina State University	Information Technology	2,395	42
Oakland Community College	Advanced Manufacturing	976	89
Wireless Infrastructure Association	Information Technology	2,728	100

Source: Quarterly Progress Reports (QPRs). Data reported as of 3/31/24 except for one grantee reporting as of 12/31/23.
Notes: Scaling Apprenticeship (N=4); Closing the Skills Gap (N=12). Thirteen Scaling Apprenticeship grantees and three Closing the Skills Gap grantees continued grant activities beyond 3/31/24. All three Closing the Skills Gap grantees had periods of performance ending in February 2025, almost a year after these data were collected. The last Scaling Apprenticeship grants closed in July 2024, thus the 3/31/24 QPRs reflect most of their grant periods. Four grantees operating in study states were excluded from the analysis due to either insufficient data or the lack of available comparison group members in matching counties and quarter of entry: Alamo Community College District, Argentum, H-CAP, Inc, and Southern Utah University.

Formation of Treatment Group and Impact Study Sample

Apprentice Inclusion Criteria

The impact study sample included apprentices who enrolled with an impact study grantee between July 1, 2021, and June 30, 2022, and met the following criteria:

1. Has a valid SSN in WIPS,
2. Has accessible data on their county of residence provided by their grantee,
3. Has comparison group members who lived in the same county and enrolled in the same calendar quarter, such that they could be matched to at least one of the two comparison groups (Wagner-Peyser participants and community college students).

Only individuals with a valid SSN could be matched to the records in the NDNH to obtain pre- and post-enrollment earnings and employment. Therefore, any apprentice who did not have an SSN listed was dropped from the sample.

As described in the next chapter, the matched comparison group strategy included matching apprentices to comparison group members that lived in the same county and enrolled in Wagner-Peyser services or a community college in the same quarter. Matching on county allowed the evaluation team to control for a set of unobservable characteristics associated with where people live, the labor market conditions they faced both before and after receiving services, and alternative services available to them. Matching on quarter of enrollment allows the evaluation team to control for time-varying economic trends. The WIPS data does not include information on county of residence for Scaling Apprenticeship and Closing the Skills Gap grant participants. The evaluation team thus needed to collect data on apprentices' county of residence directly from the individual grantees. The analysis sample excludes apprentices for whom the team could not collect county of residence data. In contrast, this was not an issue for the comparison groups because the WIPS data includes information on county of residence for Wagner-Peyser participants, and the team collected county data from community colleges for college students.

For the community college comparison, we further limited the sample to apprentices who enrolled between January 1, 2022, and June 30, 2022. This is because we obtained data use agreements with community colleges later in the study timeline and therefore were unable to collect sufficient pre-enrollment earnings for the comparison group.

An important feature of our matching strategy is that a given registered apprentice could be in the analysis sample that is compared with Wagner-Peyser participants, the analysis sample compared with community college students, both, or neither. That is, the sample of registered apprentices in the Wagner-Peyser comparison is not the same as the sample of registered apprentices in the community college comparison, but neither are the two samples fully distinct. The same approach applies to unregistered apprentices: They could be in the analysis sample for either of the two comparison groups, both, or neither. Because our data collection and matching strategy depend on geography, the geographic location of an apprentice played a key role in determining which analyses they were in. We discuss our data collection and matching strategy in more detail in Chapter 4 and in the Technical Appendix.

Comparison of Full Sample and Analysis Samples

Because apprentices in the impact samples had to be in an impact study state and meet all criteria outlined above to be included in the analysis, they could potentially differ from the full group of apprentices. Table 3.2 shows the characteristics of registered apprentices in the full sample compared with registered apprentices in the analysis samples that were compared with Wagner-Peyser and Community College participants. Table 3.3 shows the same comparisons for unregistered apprentices. This section compares different samples of apprentices to illustrate how the treatment group samples differed from each other and from the larger population of apprentices. The technical appendix describes differences between treatment samples of apprentices and the comparison groups they were contrasted with.

Compared with the full sample, the analysis sample of apprentices used in for the Wagner-Peyser contrast includes a larger share of registered apprentices who are male, non-Hispanic white, non-Hispanic Black, and those with either less than a high school diploma, a high school diploma or GED, or a postsecondary certificate (table 3.2). Conversely, the analysis sample includes a smaller share who are Hispanic, youth (ages 17-24), and those with at least a bachelor's degree; these differences are all statistically significant. The analysis sample of apprentices used for the community college contrast includes a larger share of registered apprentices who are non-Hispanic Black and those with at least a bachelor's degree, and a smaller share who are non-Hispanic white and those who have only a high school diploma or some college.

Table 3.2

Comparison Between All Registered Apprentices and Registered Apprentices in Impact Study Analysis Samples

Characteristic	All Registered Apprentices	Registered Apprentices in Analysis Sample for Wagner-Peyser Contrast	Registered Apprentices in Analysis Sample for Community College Contrast
Sex			
Male	56%	69%***	56%
Female	43%	31%***	44%
Race/Ethnicity			
Hispanic	16%	10%***	15%
Non-Hispanic Asian	6%	3%***	6%
Non-Hispanic White	52%	57%***	38%***
Non-Hispanic Black	17%	24%***	35%***
Mixed/other race/ethnicity	2%	2%	0%
Missing Race	8%	4%***	4%***
Age			
17-24	35%	30%***	37%
25-29	23%	22%	25%
30-39	25%	24%	24%
40-49	11%	15%	10%
50+	6%	8%	5%*
Highest Education			
Less than High School Diploma	4%	5%**	1%***
High School Diploma or GED	4%	6%**	3%
High School Graduate	36%	36%	34%**
Some College	16%	15%	12%***
Educational Certificate	2%	5%***	2%**
Associate's degree	7%	7%	7%
Bachelor's Degree or Higher	30%	27%***	42%***
Disability Status			
Not Identified as Disabled	97%	97%***	98%
Disabled	3%	4%***	3%
Veteran Eligibility			
Not Eligible	92%	94%	95%***
Eligible	6%	6%	5%***
Low-income Status			
No	95%	96%**	97%***
Yes	2%	4%***	3%
Ex-offender Status			
Non-Ex-offender	99%	99%	N/A
Ex-offender	1%	1%	N/A

Source: Workforce Integrated Performance System (WIPS).

Notes: Full sample N=21,443; Wagner-Peyser sample N=1,271; Community Colleges sample N=1,124

Full sample includes observations from all states. Wagner-Peyser sample include observations from Alabama, Connecticut, Florida, Indiana, Michigan, Missouri, New Jersey, Pennsylvania, and Utah; the community college sample includes observations from schools in eight states (Alabama, California, Illinois, Indiana, Missouri, New Jersey, Ohio, and Texas).

N/A: data is not available.

Percentages may not sum to 100 due to rounding.

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Compared with the full sample, the analysis samples of apprentices used in the Wagner-Peyser and Community College contrasts include a significantly larger share of unregistered apprentices who are female (table 3.3), although a larger share of the full sample has missing sex. For both analysis samples, there are significant differences by race and ethnicity except for non-Hispanic Blacks and mixed/other race in the analysis sample for the Wagner-Peyser contrast. Significantly fewer unregistered apprentices in the analysis sample for the Wagner-Peyser contrast are youth. Significantly fewer unregistered apprentices in both samples have some college or a bachelor's degree or higher, and a larger share sample for the Community College contrast have a high school diploma.

TABLE 3.3

Characteristics of All Unregistered Apprentices and Unregistered Apprentices in Impact Study Analysis Samples

Characteristic	All Unregistered Apprentices	Unregistered Apprentices in Analysis Sample for Wagner-Peyser Contrast	Unregistered Apprentices in Analysis Sample for Community College Contrast
Sex			
Male	70%	80%***	75%***
Female	22%	20%*	25%
Missing	8%	0%***	0%***
Race/Ethnicity			
Hispanic	11%	7%***	5%***
Asian	6%	2%***	5%**
Non-Hispanic White	60%	58%*	48%***
Non-Hispanic Black	14%	23%	36%**
Mixed/other race/ethnicity	2%	3%	2%
Age			
17-24	41%	31%***	45%
25-29	15%	16%	13%
30-39	21%	26%	20%
40-49	13%	16%	14%
50+	10%	11%	9%
Highest education			
Less than high school diploma	6%	6%	6%
High school diploma or GED	6%	12%	5%
High school graduate	27%	28%	37%***
Some college	28%	21%***	32%*
Educational certificate	4%	8%	5%
Associate's degree	6%	7%	7%
Bachelor's degree or higher	22%	19%***	9%***
Disability status			
Not disabled	98%	98%	98%
Disabled	2%	2%	3%
Veteran eligibility			
Not Eligible	93%	93%***	95%***
Eligible	7%	7%	5%***
Low-income status			
No	92%	87%	90%***
Yes	7%	13%***	10%**
Ex-offender status			
Non-ex-offender	97%	95%	N/A
Ex-offender	3%	5%	N/A

Source: Workforce Integrated Performance System (WIPS).

Notes: Full sample N=12,456; Wagner-Peyser sample N=950; Community Colleges sample N=594.

Full sample includes observations from all states; the Wagner-Peyser sample include observations from Alabama, Connecticut, Florida, Indiana, Michigan, Missouri, New Jersey, Pennsylvania, and Utah; the community college sample includes observations from schools in eight states (Alabama, California, Illinois, Indiana, Missouri, New Jersey, Ohio, and Texas).

N/A: data is not available.

Percentages may not sum to 100 due to rounding.

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

As described above, geographic location played an important role in determining whether a given apprentice was included in one or both analysis samples (Wagner-Peyser comparison and community college comparison). For example, because we able to collect both Wagner-Peyser and community college data from Missouri, an apprentice in Missouri could have been in both analysis samples; whereas an apprentice in Texas data could be in the community college comparison sample but could not be in the Wagner-Peyser comparison sample because we did not collect data on Wagner-Peyser participants in Texas. Table 3.4 illustrates how each of the four analysis samples were distributed across states, where states are listed in descending order by sample size in each column. Chapter 4 and the Technical Appendix discuss our data collection and matching strategy in greater detail.

TABLE 3.4
Geographic Distribution of Analysis Samples

Registered Apprentice Analysis Sample for Wagner-Peyser Comparison		Registered Apprentice Analysis Sample for Community College Comparison		Unregistered Apprentice Analysis Sample for Wagner-Peyser Comparison		Unregistered Apprentice Analysis Sample for Community College Comparison	
State	Percent	State	Percent	State	Percent	State	Percent
Missouri	35%	Texas	41%	Indiana	39%	Missouri	36%
Indiana	20%	Missouri	15%	Missouri	34%	Indiana	21%
Florida	12%	Florida	7%	Florida	6%	Alabama	18%
Michigan	10%	Indiana	5%	Michigan	6%	Ohio	12%
Pennsylvania	10%	New York	5%	Alabama	5%	Texas	4%
All others (4 states)	13%	All others (21 states)	27%	All others (4 states)	10%	All others (10 states)	9%

Source: Workforce Integrated Performance System (WIPS)
Notes: Registered Apprentice Wagner-Peyser comparison sample N=1,271; Registered Apprentice Community Colleges comparison sample N=1,124; Unregistered Apprentice Wagner-Peyser comparison sample N=950; Unregistered Apprentice Community Colleges comparison sample N=594. States are sorted in descending order of the proportion of the analysis sample. As described in the appendix, the study included students living in states other than the one their college was in, but only in the case of Ohio colleges, where this was widespread in the data. For example, a student could be enrolled in remote learning in Ohio while living in New York; an apprentice living in New York could be matched to that student.

Chapter 4: Comparison Group Selection and Matching Process

This chapter describes the comparison groups selected for the matched comparison group design: Wagner-Peyser program participants and people attending community college for occupational training in apprenticeship industries. As noted above, these are two common pathways that workers use to improve their labor market outcomes, and apprenticeship represents a third pathway.

Using two comparison groups, each representing a potential counterfactual for apprenticeships, provides a more robust picture of how apprenticeship compares to two other common pathways, not just one. Consistent with this, we present results for each outcome as two separate impact estimates, one for each comparison group. In cases where the two impact estimates differ meaningfully, we discuss what factors specific to the comparison group may have led to these differences.

The chapter first explains why we selected these two groups as the “counterfactual” to an apprentice and the process by which we selected the comparison groups. It then describes the matching process, the sample balance, the impact estimation methodology, and limitations.

Since our research questions focus on the impacts of registered and unregistered apprenticeship separately, we have four primary impacts: registered apprentices compared with a Wagner-Peyser comparison group, unregistered apprentices compared with a Wagner-Peyser comparison group, registered apprentices compared with a community college comparison group, and unregistered apprentices compared with a community college comparison group.

Wagner-Peyser Program Comparison Group

In 1933, the Wagner-Peyser Act established a system of public employment offices called the Employment Service. In 2014, the Workforce Innovation and Opportunity Act amended Wagner-Peyser to create a one-stop delivery system by co-locating the Employment Service with the AJC network (Employment and Training Administration, n.da). Together, the Employment Service and AJC network provide services to job seekers including job search and placement assistance, career guidance, information on labor markets, assessments, and access to training opportunities and programs (Employment and Training Administration, n.db). Almost all Wagner-Peyser participants receive basic career services; over half receive staff-assisted job search services, and half receive workforce information services. Most participants are engaged for four or fewer weeks (Office of Policy Development and Research 2025).

Individuals seeking to improve their labor market outcomes may be referred to apprenticeship programs by an AJC or other public workforce agency partners. In the absence of an available apprenticeship program, these individuals would presumably be referred to another workforce development program or service, such as the Employment Service. Wagner-Peyser participants and the services they receive from the public workforce system are included in the WIPS data. Like apprenticeship programs, these workforce services help participants to enter employment and increase earnings. Workers generally seek out Wagner-Peyser services for assistance in pursuing a new job. Most Wagner-Peyser participants are unemployed when they seek services and receive only light-touch case management or job search assistance. Wagner-Peyser participants with similar levels of education, prior earnings, and geographic location constitute an appropriate comparison group for apprentices. We formed comparison groups for this group from data from nine state workforce agencies: Alabama, Connecticut, Florida, Indiana, Michigan, Missouri, New Jersey, Pennsylvania, and Utah.

Community College Comparison Group

Community colleges are public colleges that primarily award associate's degrees and offer some non-degree programs.[27] Generally, community colleges are open-access or have low barriers to entry and therefore serve a wide population. Almost half of community college students are older than 24, and over a quarter have dependents. Most community college students attend part-time and work while enrolled (Community College Research Center 2021).

Many individuals pursue postsecondary education to enhance their labor market skills and increase their future earnings potential. Community college students may take courses similar to those in apprenticeship programs and have similar background characteristics and prior earnings as apprentices. This group is also an appropriate comparison group, as site visit grantees reported they recruited apprentices from community college student bodies or conducted outreach to high school seniors who planned to enroll upon graduating. These individuals may have attended a community college in the absence of an apprenticeship program. Thus, a subset of community college students

[27] Some states include two-year colleges that primarily offer associate degrees and some bachelor's degrees in their definition of community college.

likely represents an appropriate comparison group for many apprentices.[28] Data for the comparison group came from eight community colleges systems from eight states: Alabama, California, Illinois, Indiana, Missouri, New Jersey, Ohio, Texas.

To further ensure that the community college sample most closely represented a counterfactual for apprentices, we limited the comparison group to community college students who were studying in training fields that were covered by the apprenticeships.

Process for Selecting Comparison Group Members

To create the Wagner-Peyser and community college comparison groups, we began with all individuals in each group for whom the necessary data elements were available. The basic procedure was as follows:

- The Wagner-Peyser comparison group began with all participants who enrolled in Wagner-Peyser Employment Services from July 1, 2021, through June 30, 2022, and lived in a state with programs operating under one or both grants and agreed to share data with the study team.
- The community college comparison group began with all community college students who shared a combination of geographic location (county), field of training, and college enrollment during a two-quarter period with at least one apprentice.

Matching and Weighting

The goal of the impact study was to provide causal estimates of the effect of participating in either a registered or unregistered apprenticeship program under the grants on apprentices' earnings and employment outcomes. To that end, we relied on a "selection-on-observables" assumption that participation in an apprenticeship was effectively random once we accounted for observed characteristics related to both program participation and the outcomes of interest (Imbens 2004). Important observable variables were apprentices' earnings and employment history, which help

[28] We use the term "community college" for ease of exposition. We obtained data from individual community colleges, state-wide community college systems, and state-wide higher education systems. Therefore, some individuals in our community college comparison group attended public, four-year institutions that are not community colleges.

account for other latent factors (e.g., motivation) that are not directly observable but influence selection into apprenticeship and are causally related to employment. We created comparison groups that were as similar as possible to each treatment group by applying inverse probability weights (IPW), which assigned greater weight to potential comparison group members who were more similar to apprentices than to those less similar (Horvitz and Thompson 1952).

We calculated IPWs by using a "propensity score" (Rosenbaum and Rubin 1983) that estimated the likelihood of an individual's participation in an apprenticeship based on pre-enrollment characteristics. We estimated weights separately for each combination of treatment group (registered apprentices and unregistered apprentices) and comparison group (Wagner-Peyser participants and community college students). The use of IPWs in non-experimental designs has been shown to perform well in real-world settings when there is strong overlap of the propensity score across the treatment and comparison groups (Busso et al. 2014; Huber et al. 2013). After calculating the IPWs, we applied an additional weighting adjustment to ensure the number of weighted comparison individuals was the same as the number of apprentices in each county and year-quarter of entry (see the technical appendix for additional details). We ensured exact balance in the timing of program enrollment to account for macroeconomic factors that could have influenced the decision to enroll, earnings, and employment. In addition, we ensured perfect balance in county of residence to prevent bias from differences in labor market conditions.

Finally, to generate IPWs, we set weights equal to one for all apprentices and equal to $\hat{p}_i/(1-\hat{p}_i)$ for the comparison group, where $\hat{p}_i$ is the estimated propensity score. To create final IPWs, we adjusted the weights such that the sum of all weights was equal for the treatment and comparison groups in each county and quarter of entry.

Sample Matching and Balance

The impact study includes 1,271 registered apprentices matched to at least one member of the Wagner-Peyser comparison group and 1,124 registered apprentices matched to at least one member of the community college comparison group. It also includes 950 unregistered apprentices matched to at least one member of the Wagner-Peyser comparison group and 594 matched to at least one member of the community college comparison group.

Among the Wagner-Peyser comparison group, 260,713 are matched to at least one registered apprentice (Technical Appendix table A.5) and 32,642 are matched to at least one unregistered apprentice (Technical Appendix table A.7). Among the community college comparison group, 4,360 are matched to at least one registered apprentice (Technical Appendix table A.6) and 3,076 are matched to at least one unregistered apprentice (Technical Appendix table A.8). These comparison group members are then weighted based on the IPWs described in the previous section.

After forming the analytic sample of treatment and comparison group members through the process described above, we assessed the balance of each treatment-comparison group combination to evaluate their similarity. Assessing balance is a critical step in determining whether IPWs created two groups that are similar in their characteristics prior to the implementation of the treatment (Stuart 2010). If the groups are imbalanced in their baseline characteristics, it may suggest that, in the absence of the intervention, their outcomes could have differed meaningfully. This would call into question the validity of the comparison group.

We assessed covariate balance by analyzing the effect size differences across key variables, providing a measure of the magnitude of differences between the treatment groups and comparison groups on a common scale across variables. We followed research guidelines in interpreting effect sizes of less than 0.25 in absolute value as indicating sufficient balance for establishing baseline equivalence and effect sizes of less than 0.05 in absolute value as indicating very strong balance. Overall, the balance between our treatment and comparison groups was strong across all four treatment–comparison group combinations. For three of the four combinations, the differences in effect sizes were all within the values considered eligible for statistical adjustment. For the unregistered apprentices-community college comparison, the comparison group was more likely to be non-Hispanic white. Detailed balancing tests are reported in the technical appendix. To account for any remaining imbalances on baseline characteristics, we used regression models that controlled for baseline characteristics to estimate the treatment effects.

Impact Estimation Method

We estimated the impacts of participating in an apprenticeship on employment and earnings using linear regression models applying our IPWs. The models included the same covariates as the propensity score model, plus county and quarter of enrollment fixed effects. This "doubly robust" strategy helps ensure unbiased estimates if either the propensity score model or regression model is correctly specified, and it has been found to perform well under a range of circumstances (Busso, DiNardo and McCray 2014; Huber, Lechner and Wunsch 2013).

When estimating impacts on earnings we included individuals with zero earnings in the sample. This prevents bias in the estimated impacts on average earnings that would arise from including only employed individuals in the analysis, and results in a consistent sample of individuals across quarters and across the earnings and employment outcomes. For more details about the regression model, see the Technical Appendix.

The estimated impacts represent the average effect of apprenticeships in the sample relative to the comparison group, also known as the average treatment effect on the treated. We estimated heteroskedasticity-robust standard errors to account for differences in the variability of employment and earnings outcomes across individuals.

Caveats

Although the study attempts to address or mitigate threats to the validity of its findings in several ways, caveats remain:

- By definition, an apprentice is someone who has been hired by an employer, or who was already employed by the apprenticeship employer, in the case of incumbent workers. This poses a challenge to quasi-experimental impact designs since an employer has agreed to hire the apprentice, a decision that is based on a variety of unobserved applicant characteristics. Many of our sample inclusion restrictions and other design choices are structured to address this limitation, by adjusting for a history of pre-program earnings and employment and other key background characteristics, but it is impossible to rule out any role of unobserved background differences between apprentices and comparison group members.
- Apprenticeship programs vary in length, with some programs lasting two years or less and others lasting over three years. As a result, the ninth quarter from program entry represents a post-completion quarter for some apprentices but not for others. It is possible that the impacts would have been higher or lower if we had picked a later quarter: some apprentices might have completed their program and might be earning higher, post-apprenticeship wages; on the other hand, other apprentices might have been further away from their treatment and the treatment effect may have lessened over time. Somewhat similarly, some individuals in the community college comparison group might have been pursuing longer-term training, such as those seeking to transfer their credits to pursue a bachelor's degree at a four-year college, and thus could still have been in training at the ninth quarter after enrollment. Of course, this

could have also been true of apprentices. The heterogeneity of apprenticeship program lengths introduces important interpretive challenges that should be kept in mind.

- As discussed in Chapter 3, the impact sample may not be representative of all apprentices supported by these grant programs. In addition, all apprentices supported by these grant programs themselves may not be representative of all apprentices in these sectors, which itself may not be representative of all apprentices across all sectors.

Chapter 5: Impacts on Employment and Earnings

This chapter answers the primary and secondary research questions: did apprenticeships have an impact on ninth-quarter employment and earnings? Did apprenticeships have an impact on employment and earnings for different subgroups of participants? It presents impact estimates of registered and unregistered apprenticeships on employment and earnings relative to two comparison groups: (1) individuals who enrolled at a community college (College analysis), and (2) individuals who received Wagner-Peyser Employment Services (Wagner-Peyser analysis). The chapter first presents employment and earnings impacts for registered apprenticeship programs, followed by unregistered programs. The next section describes impacts by subgroup for registered and unregistered programs. Technical Appendix tables A.9 and A.10 provide additional details of the analyses.

In summary, both registered and unregistered apprenticeships had large and statistically significant impacts on employment and earnings, starting in the quarter of enrollment and continuing, with few exceptions, through the ninth quarter post enrollment. This was true for apprentices relative to both the College and Wagner-Peyser comparison groups. Analyses by occupational sector and participant subgroup also demonstrate the large and statistically significant impact of apprenticeship on employment and earnings.

Employment and Earnings Impacts

This section presents the quarterly employment and earnings impacts for registered apprenticeship programs and unregistered programs in the ninth quarter following enrollment. We describe why the ninth quarter was selected in the section on research questions in Chapter 1.

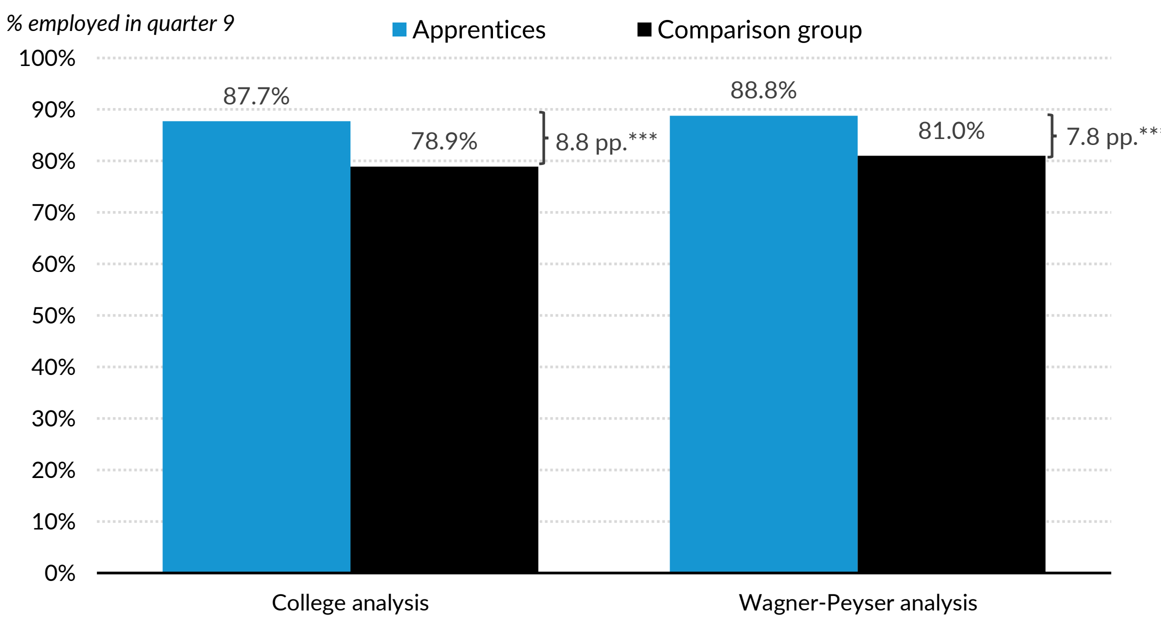
This section next describes impacts first for all registered and unregistered apprentices, then by occupational sector for registered and unregistered apprenticeships, followed by impact estimates for subgroups, again presented separately for registered and unregistered apprenticeship.

Registered Apprenticeship Impacts on Employment and Earnings

Figure 5.1 shows that registered apprenticeship programs had large, statistically significant impacts on ninth-quarter employment relative to both comparison groups. The impact of apprenticeship was similar in both analyses—increasing employment by 8.8 percentage points in the College analysis and 7.8 percentage points in the Wagner-Peyser analysis. Both impacts were statistically significant at the 1 percent level. The relative impacts—that is, the impact as a proportion of the comparison group mean—were 11.2 percent and 9.6 percent, respectively, for the College and Wagner-Peyser analyses (not shown).[29]

FIGURE 5.1

Registered Apprenticeships have Positive Impacts on Employment



URBAN INSTITUTE

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

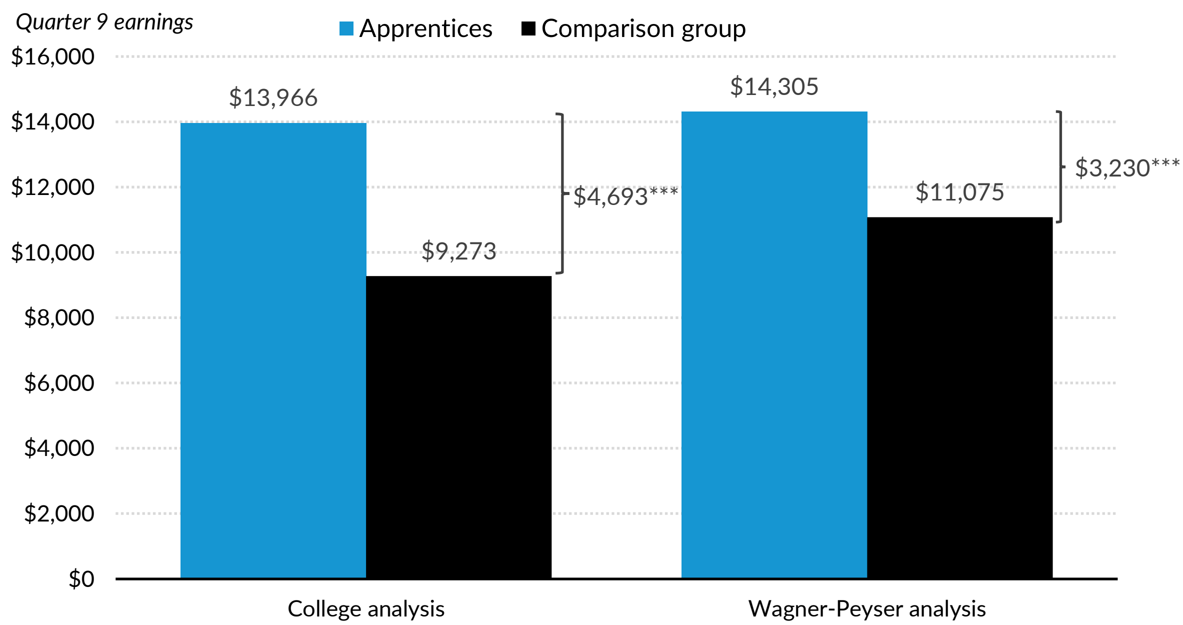
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Wagner-Peyser analysis: N=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N= 5,484 (1,124 apprentices and 4,360 community college students).

The impact of registered apprenticeships on earnings in the ninth quarter was larger in the College analysis ($4,693) than in the Wagner-Peyser analysis ($3,230) (figure 5.2). Both impacts were

[29] Note that employment rates for apprentices are their actual outcomes, whereas those for the comparison group are calculated by subtracting the estimated impact from the apprentice mean. These differ from the actual comparison group means because the estimated impacts are derived from a regression framework that controls for observable differences between apprentices and comparison group members that remain after the matching procedure. This is true for earnings estimations as well.

statistically significant at the 1 percent level. This difference was not driven by differences in treatment group earnings—as average earnings for apprentices were slightly lower in the College analysis ($13,966) than in the Wagner-Peyser analysis ($14,305). The relative impact was also higher in the College analysis than the Wagner-Peyser analysis (50.6 percent and 29.1 percent, respectively, not shown).

FIGURE 5.2
Registered Apprenticeships have Positive Impacts on Earnings



URBAN INSTITUTE

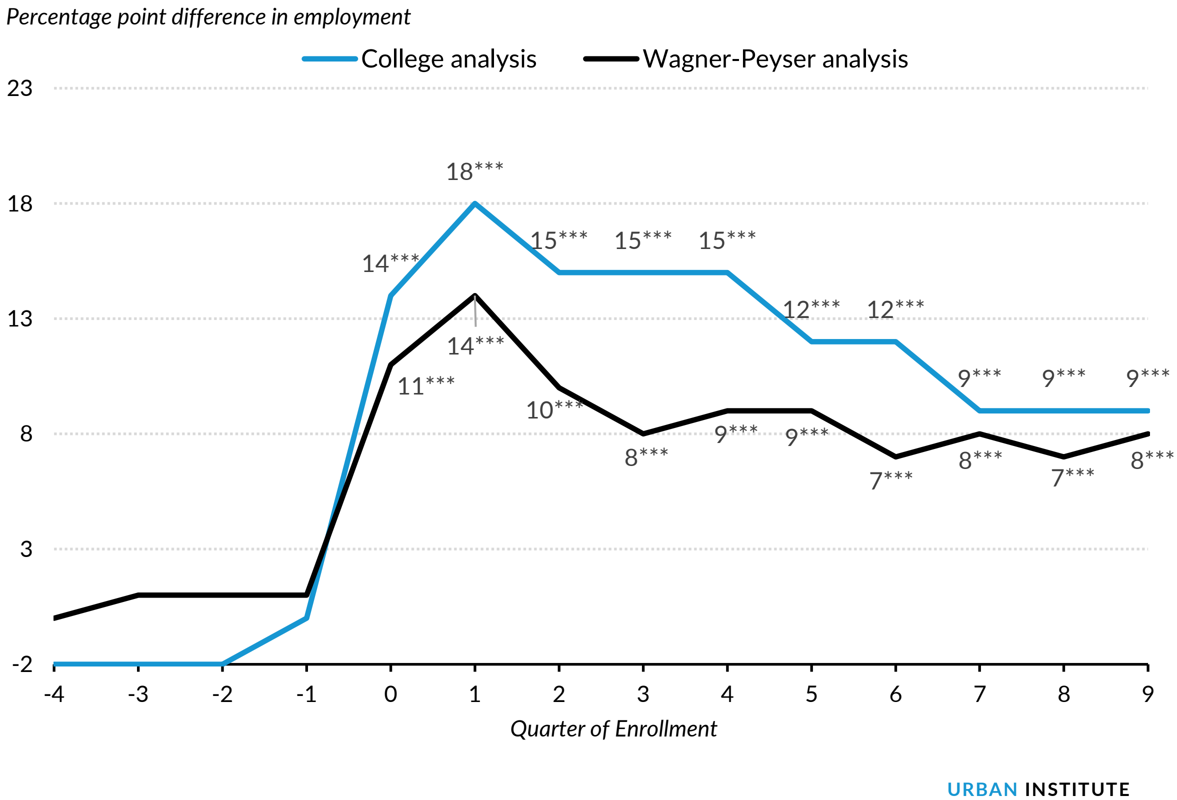
Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.
Notes: Wagner-Peyser analysis: N=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N= 5,484 (1,124 apprentices and 4,360 community college students).
Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Figure 5.3 depicts the impact of apprenticeship on employment over time. There were statistically significant impacts of apprenticeships beginning in Quarter 0 (enrollment quarter) and continuing through Quarter 9. Although the impact trends were similar for both analyses, in each quarter they were larger in the College analysis. The employment impact in both analyses was largest in Quarter 1 (18 percentage points for College analysis and 14 percentage points for Wagner-Peyser analysis). There were no statistically significant differences in employment between the apprentices and their respective comparison groups during the four quarters prior to enrollment (Quarter -4 through

Quarter -1). This is expected because the comparison groups were statistically matched to the apprentices using pre-enrollment characteristics.[30] This is true for impacts on earnings over time as well.

FIGURE 5.3

Impact of Registered Apprenticeships on Employment Over Time by Comparison Group



Source: National Directory of New Hires data matched to Workforce Integrated Performance System Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.(WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N in ninth quarter= 5,484 (1,124 apprentices and 4,360 community college students). Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

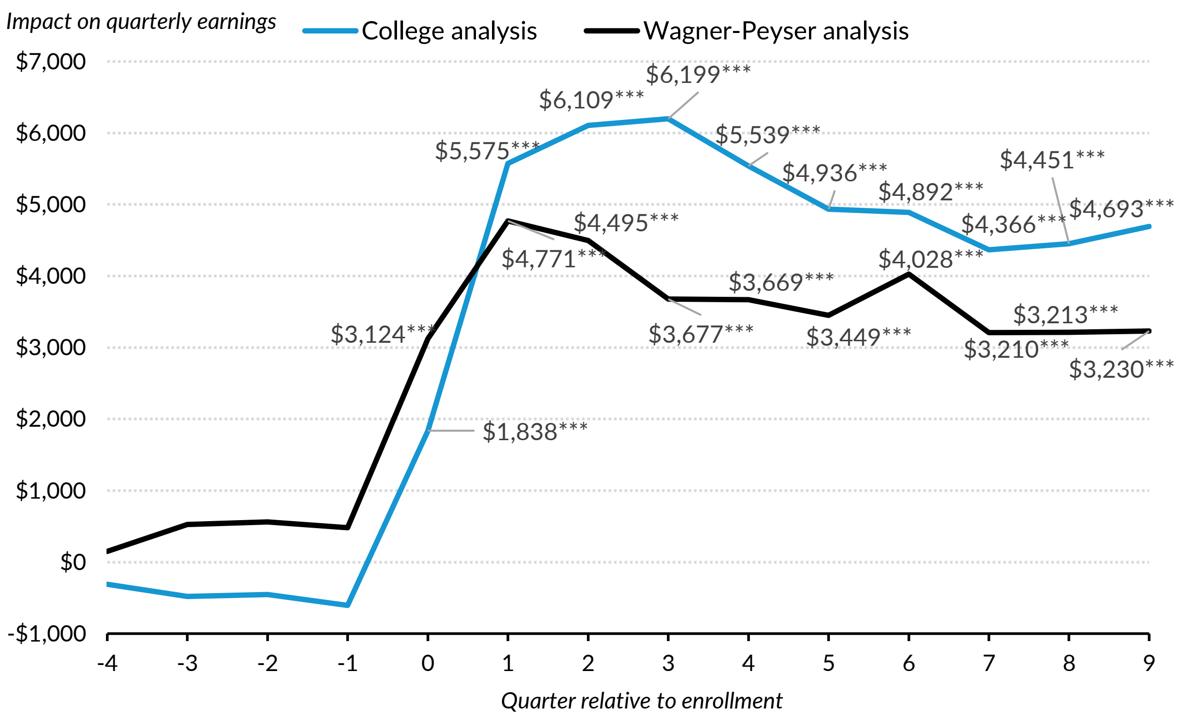
Figure 5.4 shows the impact of registered apprenticeship on earnings over time. Statistically significant earnings impacts emerged in Quarter 0 in both analyses and continued through Quarter 9. The impact was larger in the Wagner-Peyser analysis through Quarter 0; after that, it was larger in the

[30] Detailed sample balancing tests are provided in the technical appendix.

College analysis. The earnings impact was largest in the Wagner-Peyser analysis in Quarter 1 ($4,771), and in the College analysis in Quarter 3 ($6,199).

FIGURE 5.4

Impact of Registered Apprenticeships on Earnings Over Time by Comparison Group



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N in ninth quarter= 5,484 (1,124 apprentices and 4,360 community college students). Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

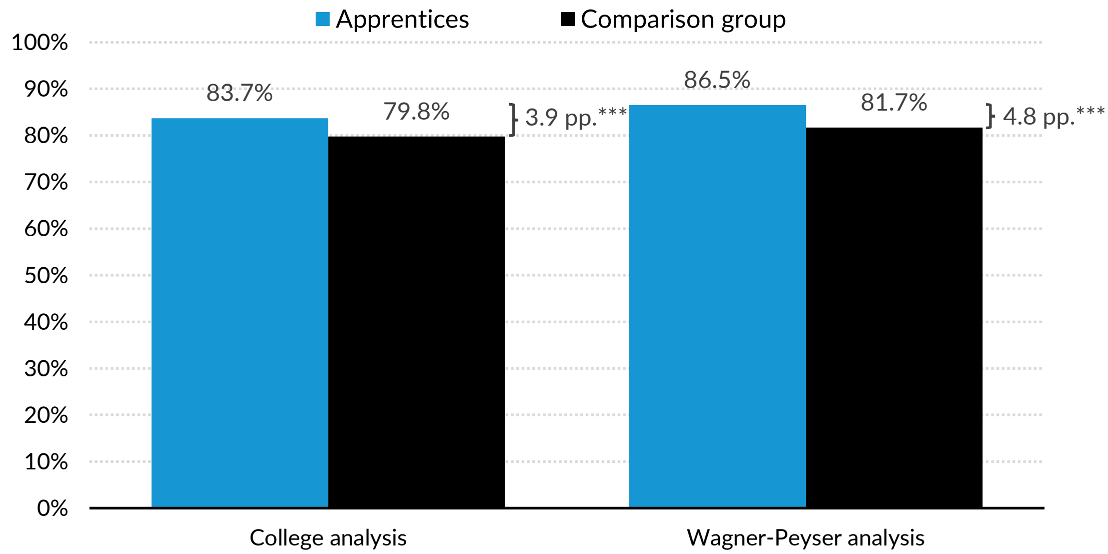
Unregistered Apprenticeship Impact on Employment and Earnings

Figures 5.5 and 5.6 show the impact of unregistered apprenticeships on employment and earnings. Figure 5.5 shows the impact on ninth-quarter employment. Unregistered apprenticeship programs had strong, significant impacts on ninth-quarter employment for both comparison groups. As shown, the ninth quarter apprenticeship employment rates were 83.7 and 86.5 percent, respectively. Unregistered apprenticeship increased employment by 3.9 percentage points in the College analysis and 4.8 percentage points in the Wagner-Peyser analysis. Both impacts were statistically significant at the 1 percent level. The relative impacts of unregistered apprenticeship ranged from 5 percent in the College analysis to 6 percent in the Wagner-Peyser analysis (not shown).

FIGURE 5.5

Unregistered Apprenticeships Have Positive Impacts on Employment

% employed in quarter 9



URBAN INSTITUTE

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

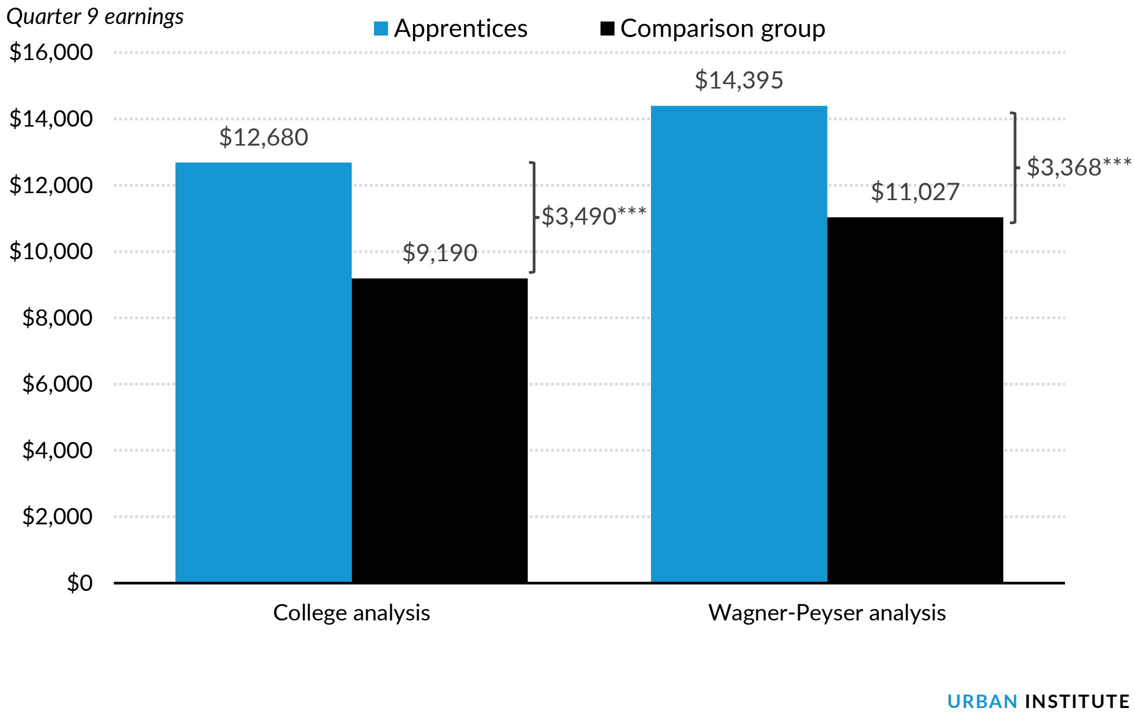
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Wagner-Peyser analysis: N=33,592 (950 apprentices and 32,642 Wagner-Peyser participants). College analysis: N= 3,670 (594 apprentices and 3,076 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Figure 5.6 shows that unregistered apprenticeships also had a significant impact on ninth-quarter earnings. Apprentices in the College and Wagner-Peyser analyses earned $12,680 and $14,395, respectively, in the ninth quarter post-enrollment. The earnings impacts ($3,490 and $3,368) were statistically significant at the 1 percent level. The relative impact of unregistered apprenticeship was 31 percent in the College analysis and 38 percent in the Wagner-Peyser analysis (not shown).

FIGURE 5.6

Unregistered Apprenticeships Have Positive Impacts on Earnings



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

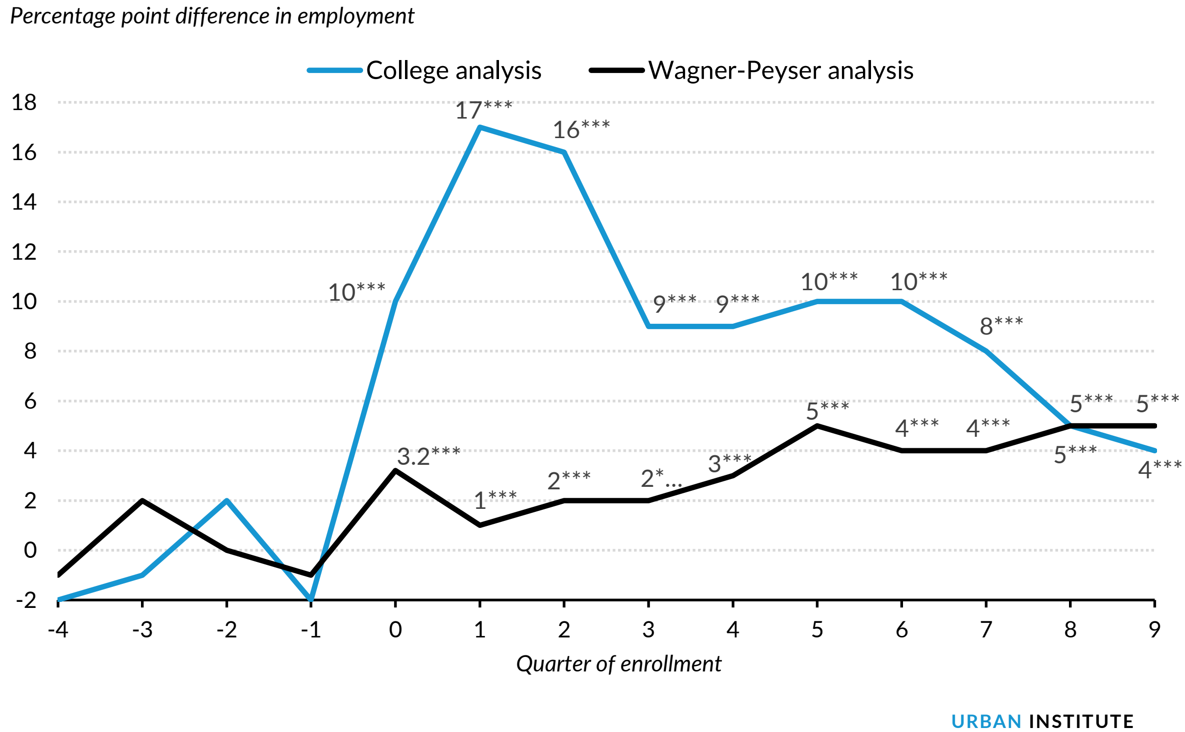
Notes: Wagner-Peyser analysis: N=33,592 (950 apprentices and 32,642 Wagner-Peyser participants). College analysis: N= 3,670 (594 apprentices and 3,076 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Figure 5.7 compares the mean quarterly employment impacts for unregistered apprenticeship over time. In the enrollment quarter (Quarter 0), unregistered apprenticeship had a significant and positive impact on employment for both analyses, which continued through Quarter 9. However, the trends in earnings impacts differed significantly for the two comparison groups. For the College analysis, employment impacts were largest in Quarter 1 (16.5 percentage points) and then decreased over time, with the smallest impact in the Quarter 9. In contrast, for the Wagner-Peyser analysis, the impact estimates trended upward with the largest impact appearing in Quarter 8 (5.1 percentage points). This may reflect the fact that many community college students are not employed while they are enrolled in college. As expected, there were no statistically significant differences in employment between the apprentices and their respective comparison groups during the four quarters prior to enrollment because comparison groups were statistically matched to the apprentices using pre-enrollment characteristics.[31] This is true for earnings impacts as well.

FIGURE 5.7

Impact of Unregistered Apprenticeships on Employment Over Time



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=33,592 (950 apprentices and 32,642 Wagner-Peyser participants). College analysis: N=3,670 (594 apprentices and 3,076 community college students).
Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

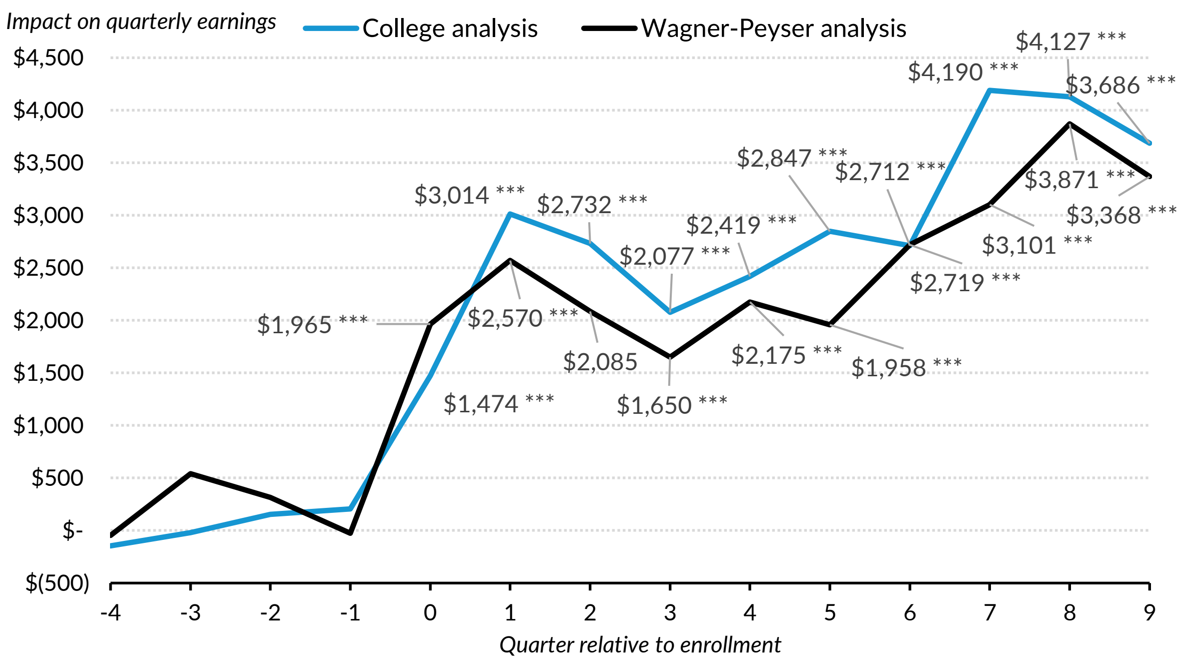
Figure 5.8 shows the mean quarterly earnings impacts of unregistered apprenticeship over time. As with employment impacts, statistically significant quarterly earnings impacts started in Quarter 0 for both analyses and continued through Quarter 9. In contrast to the employment impacts, the earnings impacts were similar and trended upward over time for both analyses. The largest impact occurred in Quarter 7 in the College analysis ($4,190) and in Quarter 8 in the Wagner-Peyser analysis ($3,871). Impacts were statistically significant at the 1 percent level. There were no statistically

[31] Detailed sample balancing tests are provided in the appendix.

significant impacts on earnings in the four quarters prior to enrollment (Quarter -4 through Quarter -1).

FIGURE 5.8

Mean Earnings Impacts of Unregistered Apprenticeships Over Time



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=33,592 (950 apprentices and 32,642 Wagner-Peyser participants). College analysis: N in ninth quarter=3,670 (594 apprentices and 3,076 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Impacts by Occupation

The prior section described the overall impact of apprenticeships on employment and earnings. This section further explores the impact of apprenticeships by examining impacts by occupational sector (advanced manufacturing, IT, and health care). Because the sample size for each sector varied by comparison group, impacts are not uniformly available for every occupation. As with the prior section, impacts are reported separately for registered and unregistered apprenticeships.

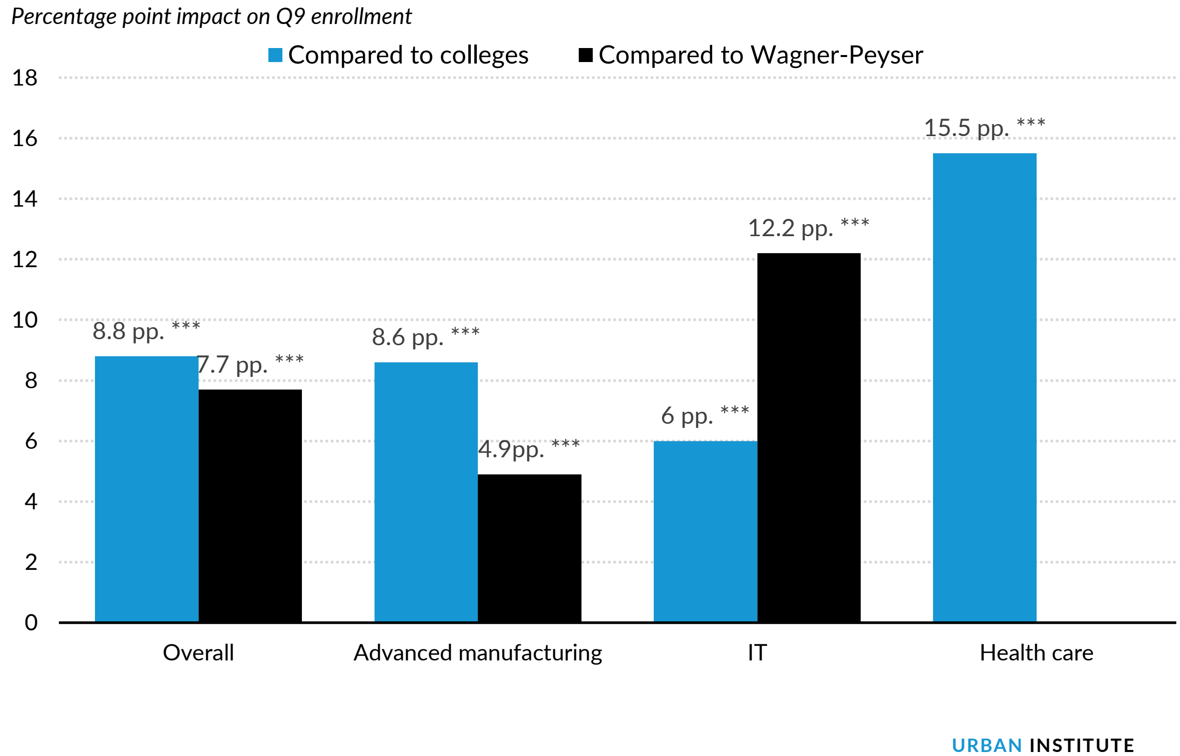
Registered Apprenticeship Impacts

Figure 5.9 shows registered apprenticeship's impacts on ninth-quarter employment overall and for each occupational sector. Advanced manufacturing registered apprenticeship programs increased ninth-quarter employment by 4.9 percentage points in the College analysis and 8.6 percentage points in the Wagner-Peyser analysis. These translate into relative impacts of 5.8 and 11.0 percent, respectively (not shown). The impacts of IT registered apprenticeships ranged from 6.0 percentage points in the College analysis to 12.2 percentage points in the Wagner-Peyser analysis, with relative impacts ranging from 8.8 to 15.2 percent, respectively (not shown). Health care registered apprenticeships had the largest impact on employment of any sector, increasing ninth-quarter employment by 15.5 percentage points in the College analysis (a relative impact of 20.2 percent).[32] All impacts were statistically significant at the 1 percent level.

[32] Sample sizes were not large enough to estimate the impact for the Wagner-Peyser analysis.

FIGURE 5.9

Impact of Registered Apprenticeships on Employment by Occupational Sector



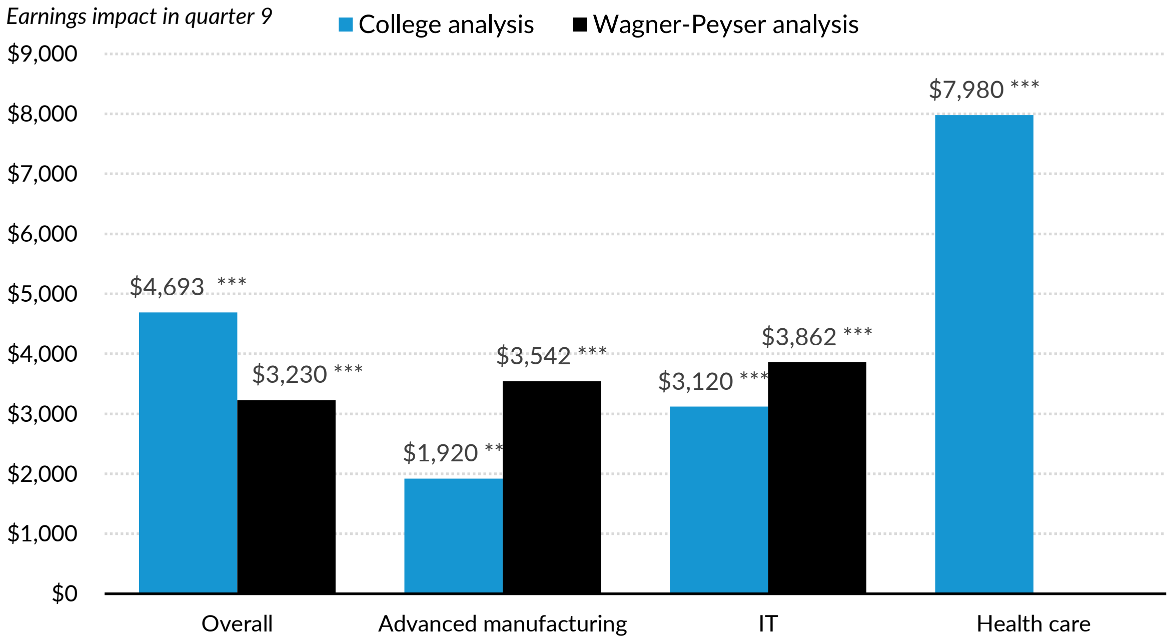
Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Wagner-Peyser analysis: advanced manufacturing N=131,130 (668 apprentices and 130,462 Wagner-Peyser participants); IT N=146,372 (432 apprentices and 145,940 Wagner-Peyser participants). College analysis: advanced manufacturing N=3,966 (246 apprentices and 3,720 community college students); IT N=3,744 (452 apprentices and 3,292 community college students); health care N=2,001 (425 apprentices and 1,576 community college students; sample sizes were not large enough to estimate the impact for the Wagner-Peyser analysis). Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Registered apprenticeship also had a significant impact on ninth-quarter earnings for each sector (figure 5.10). The impact of advanced manufacturing apprenticeships ranged from $1,920 in the College analysis to $3,542 in the Wagner-Peyser analysis (with relative impacts ranging from 16.6 to 30.2 percent respectively, not shown). Information Technology apprenticeships had earnings impacts between $3,120 and $3,862—which translate into relative impacts of 29.6 and 52.7 percent—in the College and Wagner-Peyser analyses, respectively. Finally, health care apprenticeships had the largest impact on earnings: $7,980, or a relative impact of 106.6 percent, in the College analysis. Impacts were statistically significant at the 1 percent level, except for advanced manufacturing apprenticeships in the College analysis (5 percent level).

FIGURE 5.10

Impact of Registered Apprenticeships on Earnings by Occupational Sector



URBAN INSTITUTE

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

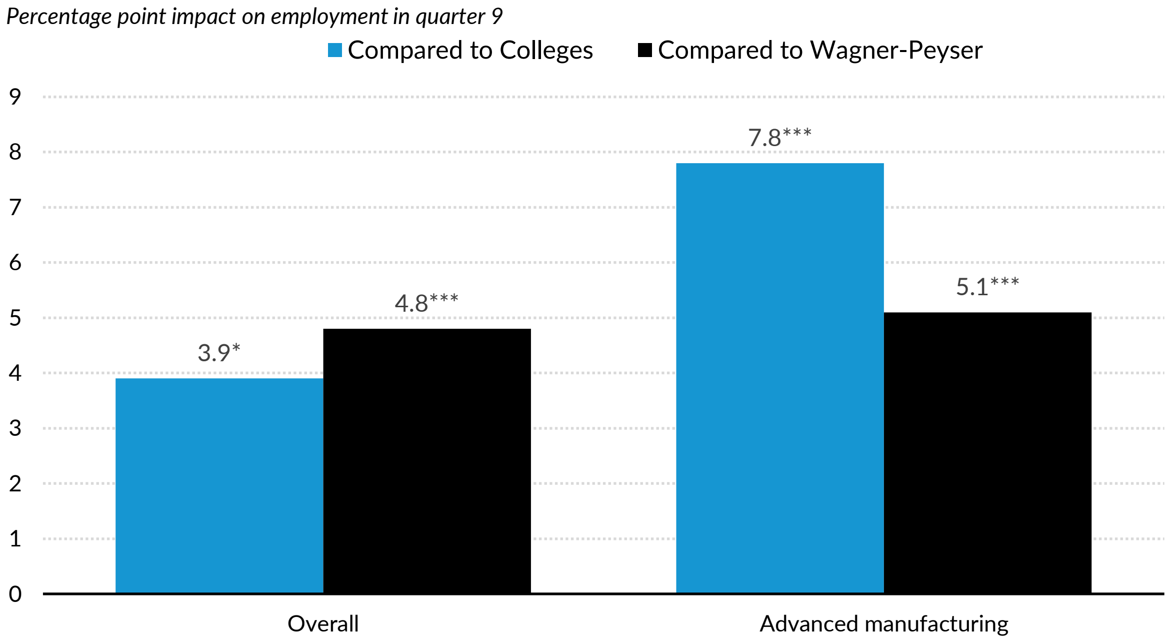
Notes: Wagner-Peyser analysis: advanced manufacturing N=131,130 (668 apprentices and 130,462 Wagner-Peyser participants); IT N=146,372 (432 apprentices and 145,940 Wagner-Peyser participants). College analysis: advanced manufacturing N=3,966 (246 apprentices and 3,720 community college students); IT N=3,744 (452 apprentices and 3,292 community college students); health care N=2,001 (425 apprentices and 1,576 community college students).
Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Unregistered Apprenticeship Impacts

Unregistered apprenticeships had a positive impact on ninth-quarter employment for all occupations (overall) and for occupations in the advanced manufacturing sector (figure 5.11). (Sample sizes were not large enough to estimate impacts for other occupational sectors.) The impacts ranged from 5.1 to 7.8 percentage points, depending on the comparison group. Impacts were significant at the 1 percent level. The relative impacts were 5.9 percent and 6.4 percent in the College and Wagner-Peyser analyses, respectively (not shown). These impacts exceed the overall impact of unregistered programs.

FIGURE 5.11

Impact of Unregistered Apprenticeships on Employment by Occupational Sector



URBAN INSTITUTE

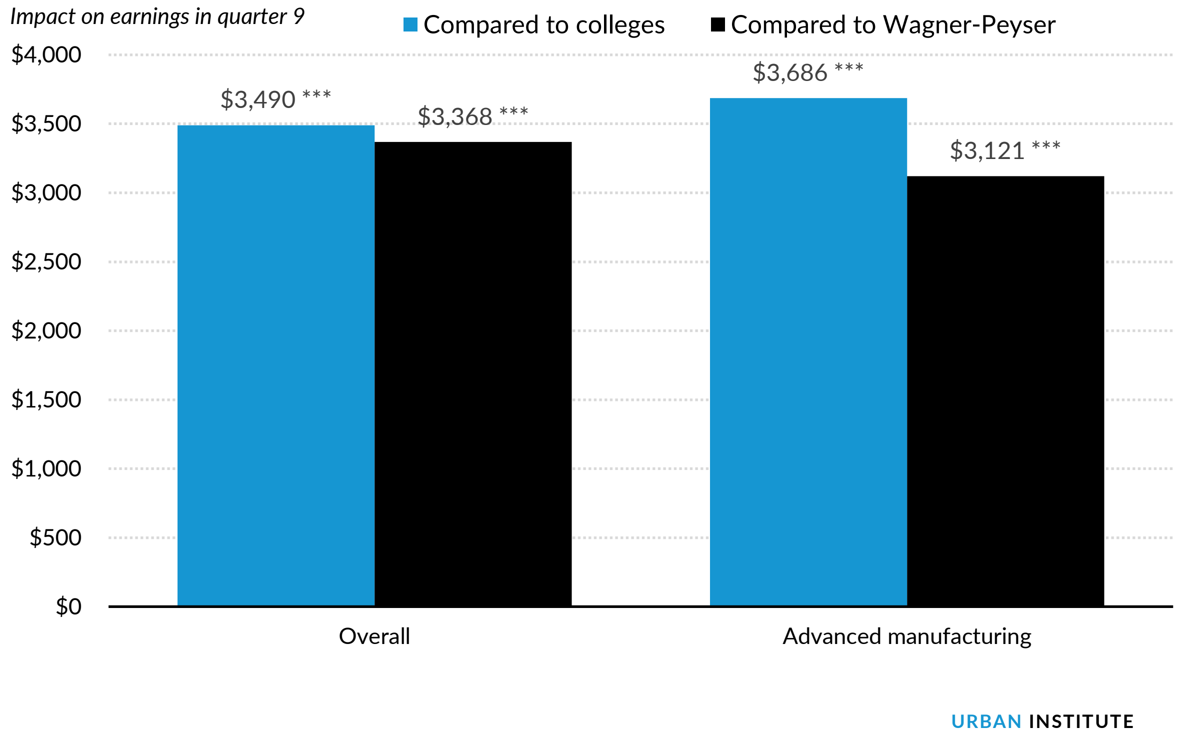
Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Wagner-Peyser analysis: advanced manufacturing N=26,297 (880 apprentices and 25,417 Wagner-Peyser participants). College analysis: advanced manufacturing N= 3,114 (479 apprentices and 2,635 community college students). Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Finally, advanced manufacturing unregistered apprenticeships had a strong impact on ninth-quarter earnings (figure 5.12). The impacts ranged from $3,121 to $3,686, depending on the comparison group, and were statistically significant at the 1 percent level. These impacts translate into relative impacts of 39.2 and 30.9 percent in the College and Wagner-Peyser analyses, respectively (not shown).

FIGURE 5.12

Impact of Unregistered Apprenticeships on Earnings by Occupational Sector



Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.

Notes: Wagner-Peyser analysis advanced manufacturing: N=26,297 (880 apprentices, 25,417 Wagner-Peyser participants). College analysis advanced manufacturing: N= 3,114 (479 apprentices, 2,635 community college students). Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Subgroup Analyses

This section continues to explore the impact of apprenticeships by examining differences across participant subgroups, including incumbent and non-incumbent workers and demographic characteristics: sex, race/ethnicity, and age. As with prior analyses, findings are presented separately for registered and unregistered apprenticeships.

Registered Apprenticeship Impacts

Incumbent and non-incumbent workers. Some apprentices, known as incumbent workers, were already employed by their sponsoring employer before beginning their apprenticeship. The impact of registered apprenticeship on ninth quarter employment for incumbent workers ranged from 5.2 to

10.6 percentage points, depending on the comparison group (table 5.1). For non-incumbent workers, the impact ranged from 6.3 to 8.7 percentage points. The impact on ninth-quarter earnings ranged from $3,742 to $6,401 for incumbent workers, and from $2,815 to $3,011 for non-incumbent workers.

TABLE 5.1

Impact of Registered Apprenticeships on Employment and Earnings in Quarter 9 by Subgroup

	College Analysis	College Analysis	Wagner-Peyser Analysis	Wagner-Peyser Analysis
Subgroup	Apprentices Mean	Impact Estimate	Apprentices Mean	Impact Estimate
Employment				
Overall	87.7%	8.8 pp.***	88.8%	7.8 pp.***
Incumbent Worker	90.1%	10.6 pp.***	91.7%	5.2 pp.***
Non-incumbent Worker	85.3%	6.3 pp.***	87.2%	8.7 pp.***
Male	86.3%	5.7 pp.***	90.3%	9.3 pp.***
Female	88.9%	11.1 pp.***	85.6%	4.9 pp.**
Non-Hispanic White	89.7%	8.5 pp.***	91.2%	8.6 pp.***
Non-Hispanic Black	86.7%	9.2 pp.***	85.4%	7.4 pp.***
Age under 25	88.3%	10.3 pp.***	85.6%	2.9 pp.
Age 25-39	89.0%	10.0 pp.***	90.8%	9.6 pp.***
Age 40 and older	N/A	N/A	89.0%	10.9 pp.***
Earnings				
Overall	$13,966	$4,693***	$14,305	$3,230***
Incumbent Worker	$15,895	$6,401***	$17,447	$3,742***
Non-incumbent Worker	$12,063	$2,815***	$12,524	$3,011***
Male	$13,949	$3,070***	$15,820	$3,655***
Female	$13,979	$5,956***	$10,970	$2,429***
Non-Hispanic White	$15,273	$4,700***	$16,260	$3,810***
Non-Hispanic Black	$12,223	$4,244***	$10,562	$2,415***
Age under 25	$13,557	$6,029***	$12,115	$2,512***
Age 25-39	$14,259	$4,350***	$14,342	$3,083***
Age 40 and older	N/A	N/A	$17,156	$4,583***

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the college analysis.

Notes: Subgroups with less than 200 treatment observations are not shown. College analysis: incumbent N=3,492 (558 apprentices and 2,934 community college students); non-incumbent N=4,678 (566 apprentices and 4,112 community college students); male N=3,001 (495 apprentices and 2,506 community college students); female N=2,483 (629 apprentices and 1,854 community college students); non-Hispanic white N=1,933 (426 apprentices and 1,507 community college students); non-Hispanic Black N=1,844 (398 apprentices and 1,446 community college students); age under 25 N=2,486 (418 apprentices and 2,068 community college students); age 25-39 N=2,183 (543 apprentices and 1,640 community college students). Wagner-Peyser analysis: incumbent N=20,575 (458 apprentices and 20,117 Wagner-Peyser participants); non-incumbent N=193,053 (811 apprentices and 192,242 Wagner-Peyser participants); male N=129,750 (874 apprentices and 128,876 Wagner-Peyser participants); female N=132,234 (397 apprentices and 131,837 Wagner-Peyser participants); non-Hispanic white N=130,869 (727 apprentices and 130,142 Wagner-Peyser participants); non-Hispanic Black N=50,776 (308 apprentices and 50,468 Wagner-Peyser participants); age under 25 N=29,596 (390 apprentices and 29,206 Wagner-Peyser participants); age 25-39 N=98,926 (589 apprentices and 98,337 Wagner-Peyser participants); age 40 and older N=133,462 (292 apprentices and

133,170 Wagner-Peyser participants). N/A: Not applicable because the apprenticeship sample size was less than 200. Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Demographic characteristics. Depending on the comparison group, the impact of registered apprenticeship on ninth-quarter employment ranged from 5.7 to 9.3 percentage points for males, and 4.9 to 11. 1 percentage points for females. The earnings impact ranged from $3,070 to $3,655 for males, and $2,429 to $5,956 for females. For non-Hispanic whites, the employment impact was about 8.5 percentage points for both comparison groups, and for non-Hispanic Blacks, it ranged from 7.4 to 9.2 percentage points. The earnings impact ranged from $3,810 to $4,700 for non-Hispanic whites, and $2,415 to $4,244 for non-Hispanic Blacks. For young workers under the age of 25, employment was 10.3 percentage points higher among apprentices than among community college students. However, the employment difference was not statistically significant when comparing apprentices to Wagner-Peyser participants. For workers ages 25 to 39, the employment impact ranged from 9.6 to 10.0 percentage points depending on the comparison group. For workers ages 40 and older, the employment impact was 10.9 percentage points in the Wagner-Peyser analysis, but the sample was too small to estimate impacts in the community college analysis. Apprenticeship also increased earnings between $2,512 and $6,029 for young workers under the age of 25, and between $3,083 and $4,350 for workers ages 25-39. For workers ages 40 and over, the earnings impact was $4,583 in the Wagner-Peyser analysis, but the sample was too small to estimate impacts in the community college analysis. For some subgroups, Hispanics, Asians, other race, and mixed race, the sample was too small to estimate impacts for either comparison analysis.

Unregistered Apprenticeship Impacts

Incumbent and non-incumbent workers. Among incumbent workers, ninth-quarter employment was not statistically different for unregistered apprentices and Wagner-Peyser participants, suggesting that unregistered apprenticeship had no impact on employment (table 5.2). The sample size was too small to compare unregistered apprentices with community college students. For non-incumbent workers, the impact was 7.1 percentage points in the Wagner-Peyser analysis and was not statistically significant in the college analysis. The impact on ninth-quarter earnings was $5,228 for incumbent workers in the Wagner-Peyser analysis, and ranged from $2,667 to $3,250 for non-incumbent workers.

TABLE 5.2

Impact of Unregistered Apprenticeships on Employment and Earnings by Subgroup

Subgroup	College Analysis Apprentices Mean	College Analysis Impact Estimate	Wagner-Peyser Analysis Apprentices Mean	Wagner-Peyser Analysis Impact Estimate
Employment				
Overall	83.7%	3.9 pp.*	86.5%	4.8 pp.***
Incumbent Worker	N/A	N/A	89.8%	3.3 pp.
Non-incumbent Worker	81.3%	3.2 pp.	85.0%	7.1 pp.***
Male	84.7%	4.0 pp.	86.2%	5.0 pp.***
Non-Hispanic White	83.7%	6.6 pp.**	88.3%	5.9 pp.***
Non-Hispanic Black	85.0%	-2.6 pp.	86.0%	3.7 pp.
Age under 25	77.3%	0.8 pp.	84.6%	-0.7 pp.
Age 25-39	N/A	N/A	90.0%	5.7 pp.***
Age 40 and older	N/A	N/A	83.3%	9.7 pp.***
Earnings				
Overall	$12,680	$3,490***	$14,395	$3,368***
Incumbent Worker	N/A	N/A	$19,414	$5,228***
Non-incumbent Worker	$10,892	$3,250***	$11,924	$2,667***
Male	$13,437	$3,817***	$14,917	$3,440***
Non-Hispanic White	$13,426	$3,536***	$14,894	$3,147***
Non-Hispanic Black	$12,167	$3,530***	$12,766	$3,813***
Age under 25	$9,684	$3,336***	$12,472	$2,926***
Age 25-39	N/A	N/A	$16,115	$3,587***
Age 40 and older	N/A	N/A	$13,918	$3,694***

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the college analysis.

Notes: Subgroups with less than 200 treatment observations are not shown. College analysis: non-incumbent N=2,469 (492 apprentices and 1,977 community college students); male N=2,338 (444 apprentices and 1894 community college students); non-Hispanic white N= 1,510 (288 apprentices and 1,222 community college students); non-Hispanic Black N=1,243 (213 apprentices and 1,030 community college students); age under 25 N=1,837 (269 apprentices and 1,568 community college students). Wagner-Peyser analysis: incumbent N=4,259 (315 apprentices and 3,944 Wagner-Peyser participants); non-incumbent N=18,130 (634 apprentices and 17,496 Wagner-Peyser participants); male N=17,494 (761 apprentices and 16,733 Wagner-Peyser participants); non-Hispanic white N=13,053 (546 apprentices and 12,507 Wagner-Peyser participants); non-Hispanic Black N=12,292 (221 apprentices and 12,071 Wagner-Peyser participants); age under 25 N=5,371 (293 apprentices and 5,078 Wagner-Peyser participants); age 25-39 N=12,506 (399 apprentices and 12,107 Wagner-Peyser participants); age 40 and older N=15,715 (258 apprentices and 15,457 Wagner-Peyser participants).

N/A: Not applicable because the apprenticeship sample size was less than 200.

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

Demographic characteristics. For males, ninth-quarter employment was 5.0 percentage points higher for unregistered apprentices compared with Wagner-Peyser participants, but not statistically different from that of community college students. The impact on ninth-quarter earnings ranged from $3,400 to $3,817. The sample was too small to estimate the impacts for females. For non-Hispanic whites, the employment impact ranged from 5.9 to 6.6 percentage points, and for non-Hispanic Blacks, the impact was not statistically significant in either comparison analysis. For non-Hispanics whites, the earnings impact ranged from $3,147 to $3,536, and for non-Hispanic Blacks, the impact ranged from $3,530 to $3,813. For young workers under the age of 25, the employment impacts were not statistically significant in either comparison analysis. The employment impact in the Wagner-Peyser analysis was 5.7 percentage points for workers aged 25 to 39 and 9.7 percentage points for those age 40 and older. For young workers under the age of 25, the earnings impact ranged from $2,926 to $3,336. The earnings impact in the Wagner-Peyser analysis was $3,587 for workers aged 25 to 39 and $3,694 for workers aged 40 and older. For these older age groups, the sample was too small to estimate employment or earnings impacts in the community college analysis. For some subgroups, females, Hispanics, Asians, other race, and mixed race, the sample was too small to estimate impacts for either comparison analysis.

Chapter 6: Conclusion

For the past decade, DOL has invested in expanding apprenticeships to nontraditional occupations—those beyond traditional fields like construction—such as health care, IT, and advanced manufacturing, and to all Americans. However, since prior research on the causal effect of apprenticeship on participants earnings and employment has focused either on the apprenticeship system as a whole (Hollenbeck and Huang 2016; Reed et al. 2012) or individual programs (Jacoby and Haskins 2020), there is little evidence on the benefits of either registered or unregistered apprenticeship in these nontraditional occupations. The Scaling Apprenticeship and Closing the Skills Gap grant programs are two federal investments in expanding apprenticeship to non-traditional occupations that provide the opportunity to advance our understanding of the benefits of registered and unregistered apprenticeship.

This impact study estimates the labor market effects of participation in registered and unregistered apprenticeship programs supported by the Scaling Apprenticeship and Closing the Skills Gap grants. Apprentices' earnings and employment are tracked, and impacts are estimated through the ninth quarter after their enrollment in the apprenticeship. This chapter first describes the key impact study findings. It then discusses the implications for efforts by DOL and others to expand apprenticeship to non-traditional occupations.

Review of Findings

The overarching impact study finding is that registered and unregistered apprenticeships had large and statistically significant impacts on employment and earnings, in the ninth quarter post enrollment. This was true for apprentices when compared with both community college students and Wagner-Peyser participants. The impacts we found for registered and unregistered apprenticeship are large in the context of earnings differentials by level of education. The four main earnings impacts (across registered and unregistered, each compared with Wagner-Peyser and community college) ranged from $3,230 to $4,693 per quarter, which is equivalent to $12,920 to $18,772 per year. These are in the same general range as the earnings differentials between people with an associate's degree and those with only a high school education, which is roughly $13,500 per year.[33] The study also found large and significant impacts on employment and earnings by occupational sector and participant subgroup.

These findings contribute to the growing evidence base on the value of apprenticeship as a viable pathway to higher-wage jobs in a range of occupations. By using two distinct comparison groups, this study offers a more robust assessment of how apprenticeship outcomes measure up against alternative pathways (college and employment services). In contrast to many previous studies, our analysis draws on a geographically diverse sample across multiple states, enhancing the generalizability of the results. Additionally, we evaluate the impact of apprenticeship participation for all individuals, not just those who complete their programs, providing a more comprehensive view of potential benefits. We also examine the outcomes associated with unregistered apprenticeship programs; however, these findings may not be generalizable to all unregistered programs because their design was shaped by criteria specified in the DOL funding announcement. Finally, our analysis includes subgroup estimates, offering insights into how the impact of apprenticeship varies across different populations. Together, these contributions offer new insights on the role of apprenticeship in today's workforce development landscape.

The employment and earnings impact estimates for the Scaling Apprenticeship and Closing the Skills Gap apprenticeship programs compare favorably to impacts estimated in other apprenticeship studies. Ninth quarter earnings impacts ranged from $3,320 to $4,693 (registered apprenticeships) and $3,368 to $3,490 (unregistered apprenticeships). By way of comparison, Reed and colleagues' 2012 study of registered apprenticeship programs in 10 states found that registered apprenticeships increased quarterly earnings by $2,182 in the sixth year post enrollment (2024 dollars). Jacoby and Haskins's 2020 impact study of unregistered apprenticeship completers found an impact on quarterly wages of $6,752 (2024 dollars). Although this exceeds our estimate, it is notable that Jacoby and Haskins focused their analyses on completers only, whereas this study included all apprentices who enrolled, regardless of completion status.

33 Based on authors' calculations using the 2023 American Community Survey. In 2023, average earnings for individuals with an associates degree was $53,089 and was $39,508 for individuals with only a high school diploma

Implications for Apprenticeship Programs and Research

The Scaling Apprenticeship and Closing the Skills Gap grantee impact study findings provide additional insight into the effectiveness of employer-based training programs—particularly apprenticeship. Based on these findings, we outline key implications for future apprenticeship programs and research below:

- **Both registered and unregistered programs have positive impacts on employment and earnings.** Much of the literature focuses on the effectiveness of registered apprenticeship programs. This study showed that unregistered programs, as well as registered ones, can have strong employment and earnings impacts. It is noteworthy that the Funding Opportunity Announcements required all unregistered programs supported by Scaling Apprenticeship and Closing the Skills Gap to incorporate components commonly associated with registered apprenticeships, including paid, work-based learning, on-the-job training and mentorship, an educational or instructional component, and an industry-recognized credential upon completion.
- **Apprenticeships in nontraditional occupations can generate positive impacts.** Although primarily used as a training model in the construction sector, the impact study results show that apprenticeship is an effective model for training individuals in other occupational sectors as well. Registered apprenticeship programs in the advanced manufacturing, IT, and health care occupational sectors produced strong employment and earnings impacts, as did unregistered advanced manufacturing programs. The findings suggest that efforts to expand apprenticeship to non-traditional occupations can be successful.
- **Apprenticeship is an effective way to train workers in high-demand occupations**. The impact study findings show that apprenticeship is a strong approach to preparing workers for high-demand occupations—particularly those facing skill shortages. Although it might seem that the same challenges driving these shortages (such as rapidly changing skill requirements or limited training opportunities) would also make it difficult to train workers, our results suggest otherwise. They provide evidence that, with the right structure and employer involvement, apprenticeship can successfully prepare American workers to meet the demands of high-growth sectors.
- **Apprenticeships are effective for both incumbent and non-incumbent workers.** Registered and unregistered apprenticeships are effective for both helping existing workers attain higher positions with their current employers (incumbent workers) and for facilitating new opportunities for workers who are new to an employer (non-incumbent workers).

- **Positive impacts are not limited to any specific worker profile.** The study found significant employment and earnings impacts by sex, race/ethnicity, and age. The size and statistical significance of the impacts differed by subgroup. However, the findings provide evidence that grantees and their partners can successfully expand apprenticeship opportunities to a broad range of Americans.

Technical Appendix

This Technical Appendix provides additional detail on several aspects of the approach used to estimate the impact of registered and unregistered apprenticeship. First, we discuss the data sources and strategies for linking data sources. Second, we provide additional details on the matching and estimation approach, including balancing tables for the treatment and comparison groups. Finally, we provide additional detailed tables supporting the results and discussion in Chapter 5.

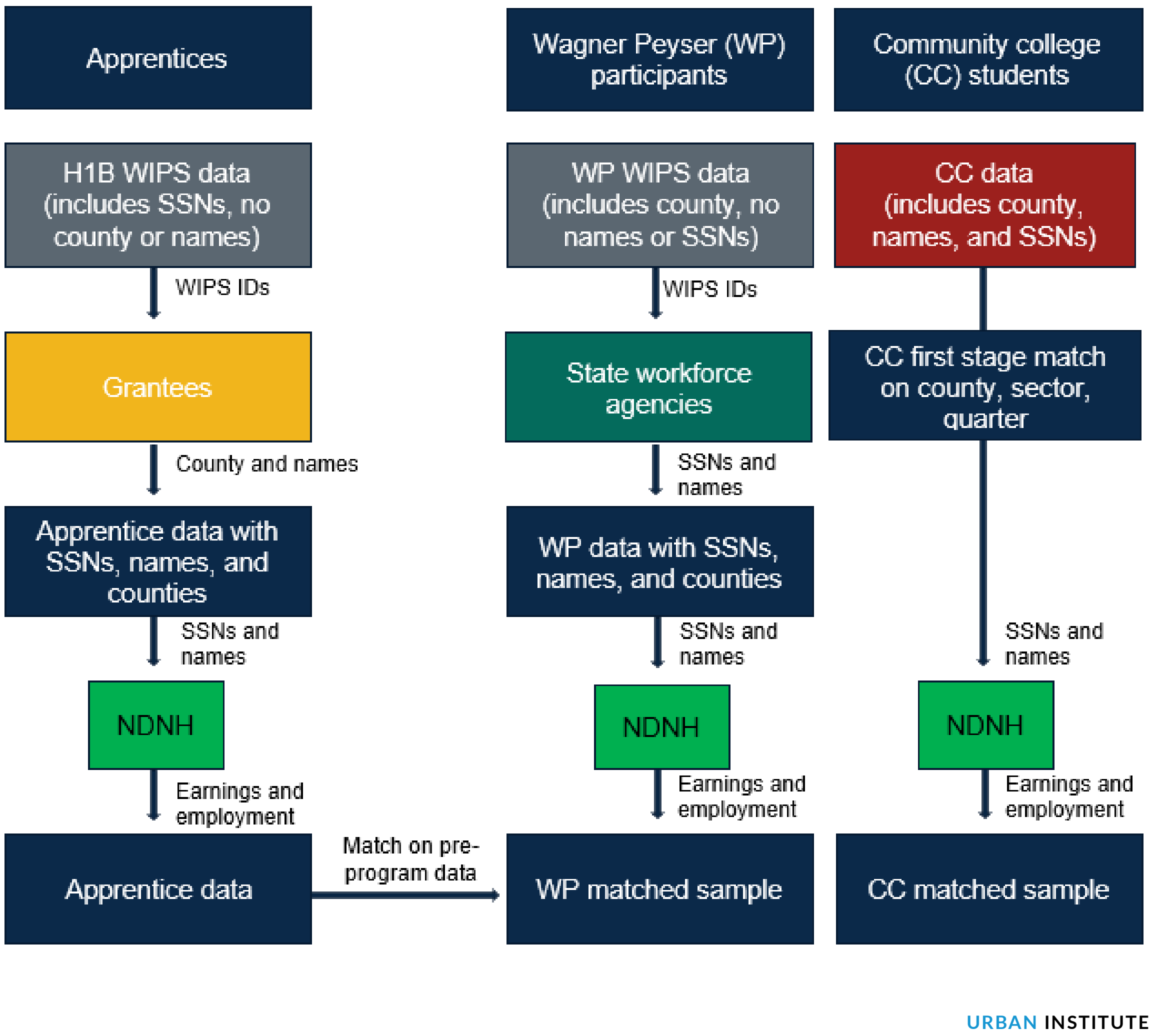
Data Sources, Data Collection, and Linkages

Technical Appendix Figure A.1 illustrates the data collection process which requires four key steps:

1. Collecting WIPS data from DOL to identify apprentices and comparison group members and their background characteristics (for the public workforce system Wagner-Peyser comparison group), and student records from community colleges (for community college comparison groups)
2. Collecting geographical data and names for apprentices from grantees
3. Collecting PII for Wagner-Peyser participants from states that participate in the study
4. Using the PII to link records with preprogram and post-enrollment data from NDNH

FIGURE A.1

Data Collection and Mapping Process by Personal Identifiable Information



Source: Authors' analysis.
Notes: AEP = Apprenticeship Evidence-Building Portfolio; AEP data = Refers to the combined dataset the project team will be using; DOB = Date of birth; NDNH = National Directory of New Hires; SSNs = Social security numbers; WIPS = Workforce Integrated Performance System.

Workforce Integrated Performance System (WIPS) Data

WIPS is a system through which DOL grantees, including Scaling Apprenticeship and Closing the Skills Gap grantees, submit program and participant data. WIPS also collects data on participants in workforce programs funded by DOL (as well as some programs funded by the Department of Education), including Wagner-Peyser Employment Services. Technical Appendix Table A.1 displays the key WIPS data items used in our evaluation. This list includes variables that may be associated with both enrollment in an apprenticeship program and labor market outcomes, such as sex, race, age, veteran status, education level, ex-offender status, and low-income status (all these fields are self-reported by the participant). To ensure data accuracy, DOL has several data integrity mechanisms in place.[34]

TABLE A.1

WIPS Data Items Required for the Evaluation

Data Category	Study Uses
Identifiers for apprentices vs. comparison group	To define the apprentice and comparison samples
Grant-funded apprentice status vs. Wagner-Peyser	
Geographic identifiers	Key information needed to select the apprentice and comparison samples from the same local areas
3-digit county FIPS code	
State code of residence	
Zip code	
Demographics and other characteristics	To construct balanced apprentice and comparison samples
Entry and exit quarters	
Age	
Race and ethnicity	
Disability status	
Education level	
Low-income status	
Ex-offender status	
Program enrollment and service receipt	To identify enrollment periods, apprenticeship types, and occupational sector
Dates of enrollment	
Apprenticeship types (registered, unregistered, incumbent, non-incumbent)	
Sector of training (apprentices only)	

Source: Authors.

Notes: AJC = American Job Centers; FIPS = Federal Information Processing Standard; WIOA = Workforce Innovation and Opportunity Act; WIPS = Workforce Integrated Performance System; Zip = Zone Improvement Plan.

[34] A detailed overview of all data elements and their definitions provided by DOL can be found at https://www.dol.gov/sites/dolgov/files/ETA/Performance/pdfs/ETA_9172_DOL_PIRL_1.18.18.pdf.

The WIPS data also includes recipients of incumbent worker training supported by DOL. However, we do not use these workers in the comparison group because they do not provide a sufficiently strong contrast with the apprentices.

Using a range of criteria described below, we submitted a request to DOL for WIPS data for (1) apprentices served by the grant program and (2) Wagner-Peyser Employment Services participants. We first received WIPS data at the beginning of 2022, and received new WIPS data twice per year, with each set of data covering two calendar quarters. The WIPS data included all Scaling Apprenticeship and Closing the Skills Gap grant participants and all Wagner-Peyser participants in the nine states with which we obtained data use agreements (Alabama, Connecticut, Florida, Indiana, Michigan, Missouri, New Jersey, Pennsylvania, and Utah).

Grantee Data

The literature suggests that credible comparison groups for quasi-experimental designs of workforce development programs require that they be obtained from the same local areas as the treatment group to balance local economic conditions and service environments (Heckman, Ichimura, and Todd 1997; Heckman et al. 1998; Glazerman, Levy, and Myers 2003). The WIPS data contains residential zip codes and county codes for the Wagner-Peyser comparison group. However, the Scaling Apprenticeship and the Closing the Skills Gap grant programs do not require grantees to submit location data to the WIPS, so the county and zip code data are not available in the WIPS for apprentices.

To gather location data on apprentices, we requested county or zip code information from grantees. We used apprentices' WIPS IDs, a unique identifier provided by grantees and also included in the WIPS data, to link the geographic information from grantees with the data items in the WIPS. When needed, we linked zip codes to the highest population share county code for the zip code in population shares using the HUD-USPS ZIP Code Crosswalk files (Wilson and Din, 2018). We requested data from grantees six times between the second quarter of 2021 and the fourth quarter of 2023.

The NDNH requests names along with SSNs (obtained from WIPS) to get a more accurate match. Grantees also provided WIPS IDs, which allowed us to link geographic data and names to WIPS data.

Community College Data

Community college data has many of the same demographic characteristics as the WIPS data. We request from community colleges student characteristics, educational history, enrollment status, and course/program information (see Technical Appendix table A.2).

All community colleges that contacted to request data participate in Title IV Federal Financial Assistance programs. Hence, they are obliged to report their institutional data to the Integrated Postsecondary Education Data System (IPEDS) of the National Center for Education Statistics in a timely and accurate manner, including key demographics like students' sex and race/ethnicity. Through their participation with IPEDS, community colleges in our sample have significant experience in preparing institutional data and reports for external use.

We negotiated DUAs with community college systems that serve as Scaling Apprenticeship and Closing the Skills Gap grantees in eight states (Alabama, California, Illinois, Indiana, Missouri, New Jersey, Ohio, and Texas). We only requested data if the community colleges could provide PII, including SSNs. The community college data itself does not contain information that would allow us to identify apprentices; however, we linked SSNs from the grantees to the community college data to identify apprentices served by the grants.

Technical Appendix table A.2 includes the list of requested variables for student-level college data:

TABLE A.2

Community College Data Requested Fields

Student characteristics
Student ID or other variable required for linking across files
First name, Last name
SSN
Date of birth
Sex
Race
Ethnicity
US citizen
English language learner
Disability status
Location (city and state, zip code, or county)
Educational history
High school completion status
Month and year of high school graduation
GED
ACT score (by category)
SAT score (by category)
Other degrees held
Enrollment status
Year of enrollment
Part time/full time
Class year/level
Transfer student
Degree program
Credit/non-credit status of program
Degrees received
Credentials received
Other expected credentials
Month and year of graduation (including expected)
Course/program information
Number of course credits completed
Primary field of study
Secondary fields of study
Course name
Course ID

Source: Authors.

Notes: GED = General Education Development tests, SAT = Scholastic Assessment Test, ACT = American College Testing (ACT).

State Workforce Data

WIPS does not include SSNs or names for Wagner-Peyser participants. To obtain these PII variables, we sent the WIPS IDs pertaining to Wagner-Peyser participants to state workforce agencies that had agreed to share data for the study. Those agencies sent us back the SSNs and names pertaining to each WIPS ID. This allowed us to link all the WIPS data elements to SSNs and names, which could then be further linked to NDNH data.

National Directory of New Hires (NDNH)

The NDNH serves as a legally mandated nationwide database housing employment, unemployment insurance, and quarterly wage data provided by state unemployment insurance (UI) agencies and federal employment records. We used the NDNH data on earnings and employment to obtain preprogram earnings of apprentices and comparison group members, as well as to measure their earnings and employment outcomes. The NDNH data contain quarterly earnings information collected by all state UI agencies and submitted to the Office of Child Support Services of the U.S. Department of Health and Human Services (Solomon-Fears 2011).

NDNH data includes most wage and salary employment but do not all types of jobs and industries. NDNH data does not include self-employed workers, railroad employees, workers in service for relatives, most agricultural labor, some domestic service workers, and part-time employees of nonprofit organizations (Czajka, Patnaik, and Negoita 2018). In prior studies, these sectors accounted for about 10 percent of U.S. employment (Hotz and Scholz 2001; Kornfeld and Bloom 1999). NDNH data also omits workers whose employers do not report their earnings to their UI agency, even in reportable sectors, because of the prevalence of flexible staffing arrangements or illegal neglect of reporting (Abraham et al. 2018; Blakemore et al. 1996; Hotz and Scholz 2001; Houseman 2001; Katz and Krueger 2016, 2019). Additionally, NDNH data does not include workers who are casually employed, such as day laborers or part-time helpers, or most work that is part of the gig economy (Abraham et al. 2018; Katz and Kruger 2016, 2019). Finally, there could be inconsistencies in reports of social security numbers (SSNs) that lead to inaccuracies in the NDNH.

Thus, an individual with no reported earnings in the NDNH data in a given quarter may have had zero earnings or may have been in one or more of the types of jobs not included in the data. We treated such observations as zero earnings, because we cannot distinguish the two scenarios and because treating such observations as missing data could have introduced greater measurement error or bias than treating the observations as missing.

We submitted personally identifiable information (PII)—that is, SSNs and when possible, first and last names—for all Scaling Apprenticeship and Closing the Skills Gap apprentices to NDNH. We submitted the same PII (SSNs and first and last names) for Wagner-Peyser participants that we collected from state workforce agencies.

NDNH deletes data older than eight quarters from its system. For all individuals submitted to NDNH, NDNH holds their available quarters of data—that is, those data are not deleted. We made early NDNH data requests for preprogram earnings soon after we received the WIPS data to hold the eight quarter-preprogram period. The first time we could submit data to NDNH was the second quarter of 2022, which limited the set of pre-program quarters we could hold. We submitted data to NDNH twice per year starting with the second quarter of 2022. In the first quarter of 2025, we submitted a "passthrough file" to NDNH to match to quarterly wage records. This file contained all variables from the WIPS, colleges, and grantees. NDNH then linked these data to their quarterly wage data, providing a dataset with all individual characteristics and available wage data.

Finally, we made some additional restrictions to the NDNH data to address what appeared to be low data coverage for certain states in the data. Specifically, we dropped state-quarters from the data for which the data match rate (any employment or UI data) was at least 30 percentage points lower than the state average. We additionally dropped data from Indiana in 2020 quarter 4, which had a very pronounced and unusual drop but did not quite cross this threshold.

Additional Details on Matching and Estimation Methods

First Stage Community College Match

The study team selected a subset of the individuals in the community college data we collected to submit to NDNH. This first-stage match for the analytical sample included candidates for the final sample. Not all individuals in the first match were ultimately included in the final sample. To be selected in the first stage match, a community college student needed to be in the same combination of county, enrollment period, and field of training as at least one apprentice (i.e., all three of constructs had to be exactly the same).

As noted above, we collected data on county of residence for apprentices from the grantees because this information is not in WIPS. For community college students, we requested this information be included with other data we collected from state higher education agencies. In some cases, grantees or agencies could only deliver zip codes. In those cases, we linked the zip codes to counties using a crosswalk from the US Census Bureau. If a given zip code linked to more than one county, we assigned the individual to the county with the largest share of population in the zip code.

Community college students typically enroll at the start of the spring or fall semester (a small number first enroll in the summer semester), while apprentices enroll continuously throughout the year (which we indexed by quarters). To define a period of enrollment that applied to both groups, we categorized the period of enrollment as either the first half of a given year (spring and summer semester enrollees for community college students, first and second calendar quarters for apprentices) or the second half (fall semester enrollees for community college students, third and fourth calendar quarters of apprentices).

An apprentice's occupation of training is categorized in WIPS using standard occupational classification (SOC) codes. Community college degree programs, majors, and courses are assigned a Classification of Instructional Program (CIP) code. To link these two, we used the US Department of Education's National Center for Education Statistics' CIP-SOC crosswalk, which links CIP codes to one or more SOC code. If available, we used the college major CIP code, otherwise we used the CIP codes associated with each course they were enrolled in. As such, a given community college student could be placed in multiple match cells: so long as there was at least one apprentice in any of their match cells, they were selected in the first-stage match. To ensure that we were not overly restrictive in the first-stage match, we used two-digit SOC codes and two-digit CIP codes, which are broader than higher digit SOC and CIP codes. Using four or six-digit codes would have resulted in a more restrictive match and could have resulted in dropping community college students who might have been strong matches.

Analysis Sample Inclusion Criteria

To be included in the analysis sample for any group (apprentices, Wagner-Peyser, or community college), each individual needed to have at least three quarters of pre-program NDNH earnings and employment data, as well as data in the ninth quarter after entry (where the quarter of entry was indexed as quarter 0, the first pre-program quarter as quarter -1, the first post-enrollment quarter as quarter 1, and so on). This restriction excluded all apprentices and comparison group members that enrolled prior to the third calendar quarter of 2021. These individuals did not have three quarters of pre-program data, because we were not able to submit data to NDNH in time for that data to be held for the study. It also excluded individuals that enrolled later than the second quarter of 2022, because these individuals did not reach their ninth post-enrollment quarter by the third quarter of 2024, the last quarter with complete data for the study. Due to the timing of when the study team was first able to collect community college data and submit it to NDNH, we were further limited to only individuals that enrolled in the first two quarters of 2022 for the community college analysis.

In addition, our analytical strategy required an exact match on period of enrollment and county. Period of enrollment was defined as the calendar quarter (for example, the third quarter of 2021) for the Wagner-Peyser contrast and as the half-year (for example, first and second quarters of 2022) for the community college contrast. Because only a single period of enrollment was eligible for the community college contrast (the first and second quarters of 2022), further exact matching on period of enrollment was not necessary for the community college contrast.

Exact matching on period of enrollment and county also excluded all apprentices for whom we did not attempt to collect county data or for whom we attempted to collect this data but were unable to do so (we describe our process for selecting grantees from which to pursue data in Chapter 3). Exact matching excluded apprentices that did not have any comparison group members in their county-enrollment period exact match cell. We collected PII on Wagner-Peyser participants from 10 states: thus, any apprentices living outside of these 10 states could not be included in the Wagner-Peyser analysis. Similarly, any apprentices living in states or counties without any community college students were excluded from the community college analysis. Exact matching was done separately for the Wagner-Peyser and community college analyses; thus, a given apprentice could satisfy this exact match criterion for the Wagner-Peyser analysis only, the community college analysis only, both, or neither. For this reason, the set of apprentices in the Wagner-Peyser analysis partially, but not fully, overlaps with the set of apprentices in the community college analysis.

Data Cleaning and Formatting

Once we collected the data, we formatted an analysis sample including data on covariates and employment outcomes. This required making some key decisions, such as the following:

- We dropped community college students from the analysis who did not live in the state of their community college. The exception to this was for the Ohio Department of Higher Education, which offered substantial remote learning opportunities. For Texas data, we further restricted students to those living in the Houston metropolitan area for San Jacinto College and to students not living in the Houston metropolitan area for Dallas College.
- Some participant characteristics had frequently missing values. For veteran status, disability status, ex-offender status, and low-income earner status, we imputed missing values to zero.

This was based on our interpretation that sometimes these variables were only filled in when the characteristic applied. For cases that were missing sex, we imputed based on the share of males in each program quarter, county, data source, and treatment status bin.

- Community college data often had less detailed education, race/ethnicity, and disability categories than in WIPS data. In these cases, we coarsened the WIPS data for matched apprentices to align with the available community college data.
- There were some community college datasets that were missing data on covariates used in the analysis, including educational background and disability status. In these cases, we removed the data for matched apprentices so that both were missing.

Propensity Score Estimation and Weighting Methods

We calculated inverse probably weightings (IPWs) by using a "propensity score" to estimate the likelihood of an individual's participation in an apprenticeship based on pre-enrollment characteristics. We estimated weights separately for each combination of treatment group (registered apprentices and unregistered apprentices) and comparison group (Wagner-Peyser participants and community college students). The use of IPWs in non-experimental designs has been shown to perform well in real-world settings when there is strong overlap of the propensity score across the treatment and comparison groups (Busso et al. 2014; Huber et al. 2013).

Double-selection Least Absolute Shrinkage and Selection Operator (LASSO). We estimated propensity scores by using a LASSO model. LASSOs select a parametric model by choosing covariates predicting the propensity score from a prespecified list of variables. The method limits the number of covariates included in a model by imposing a penalty for each covariate added. We used the double-selection LASSO method, which selects covariates based on the model's ability to predict both the outcome and whether an individual was an apprentice. The double-selection approach involved running LASSO first by using apprenticeship participation as the dependent variable; second, running LASSO by using employment in the ninth quarter following program enrollment as the dependent variable; and, finally, taking the union of covariates selected by either run of the LASSO. We ran the double-selection LASSO using the lasso package in Stata, with both LASSO regression specified as linear probability models. The penalty parameter, λ, controls the shrinkage of coefficients toward 0 and therefore influences the sparsity of the final model. To optimally set λ without losing substantial computing time to cross validation, we used a plug-in estimate for the optimal λ, assuming heteroskedastic errors, as defined by Belloni, Chernozhukov, and Hansen (2014).

Variable selection. To identify a baseline set of covariates to feed into the model, we chose a set of pre-enrollment employment and earnings measures and demographic characteristics that are likely relevant to apprenticeship participation and later labor market outcomes. First, we developed a superset of covariates which included all demographic characteristics listed in table A.3. We then developed eight potential sets of covariates, which differed based on whether they included enrollment quarter and country fixed effects, whether they included earnings squared, whether they forced the LASSO to select basic demographics, and whether they ensured an exact match (implemented through the weighting procedure) on any employment in the four pretreatment quarters. Table A.3 lists the eight sets of covariates that we considered.

TABLE A.3

Covariate Sets Considered for LASSO Inclusion

Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
County	E	E	E	E	E	E	E	E
Quarter of program entrance	E	E	E	E	E	E	E	E
State	-	-	-	-	-	-	-	-
Age	I	I	I	I	I	I	F	F
Sex	I	I	I	I	I	I	F	F
Race/ethnicity	I	I	I	I	I	I	F	F
Education level	I	I	I	I	I	I	F	F
Employed in Q0, WIPS version	I	I	I	I	I	I	I	I
Ex-offender	I	I	I	I	I	I	I	I
Disability status	I	I	I	I	I	I	I	I
Veteran status	I	I	I	I	I	I	I	I
Low income status	I	I	I	I	I	I	I	I
Has NDNH data in qm4	F	F	F	F	F	F	F	F
Earnings in quarter -1	F	F	F	F	F	F	F	F
Earnings in quarter -2	F	F	F	F	F	F	F	F
Earnings in quarter -3	F	F	F	F	F	F	F	F
Earning in quarter -4	F	F	F	F	F	F	F	F
Earnings in quarter -1 squared	I	I	I	I	F	F	-	-
Earnings in quarter -2 squared	I	I	I	I	F	F	-	-
Earnings in quarter -3 squared	I	I	I	I	F	F	-	-
Earning in quarter -4 squared	I	I	I	I	F	F	-	-
Employment in quarter -1	F	F	F	F	F	F	F	F
Employment in quarter -2	F	F	F	F	F	F	F	F
Employment in quarter -3	F	F	F	F	F	F	F	F
Employment in quarter -4	F	F	F	F	F	F	F	F
Any Employment from quarter -4 to quarter 1	F	F	E	E	E	E	-	-
Any UI benefits in quarter -1 or 0	I	I	I	I	I	I	I	I
Any UI benefits in quarter -2	I	I	I	I	I	I	I	I
Any UI benefits in quarter -3	I	I	I	I	I	I	I	I
Any UI benefits in quarter -4	-	-	-	-	-	-	I	I
Two or more employers in quarter -1	-	-	-	-	-	-	I	I
Two or more employers in quarter -2	-	-	-	-	-	-	I	I
Two or more employers in quarter -3	-	-	-	-	-	-	I	I
Two or more employers in quarter -4	-	-	-	-	-	-	I	I
County - quarter fixed effects	-	I	-	I	-	I	-	I

Note: E = Exact match, F = Force included in LASSO, I = Included in LASSO, - = not included.

Adjusting for employment shocks in the Wagner-Peyser comparison group. Because many people solicit Wagner-Peyser employment services after an earnings or employment shock, there is a risk that Wagner-Peyser participants may have been more likely than apprentices to have had such a shock in the quarter of program entry. To address this, we created an additional covariate indicating whether an individual received unemployment insurance (UI) in either the quarter prior to program entry or the quarter of program entry. This requires the assumption that program participation will not affect UI receipt in the quarter of program entry, which we believe to be valid given that neither program seems likely to increase or decrease the chance of layoff within the first month or two of the program (i.e., during the entry quarter). For analyses using the Wagner-Peyser comparison group, we therefore considered an additional specification where we limited both the treatment and comparison groups to individuals who did not receive UI in either the quarter before program entry or the quarter of program entry. For each of the registered and unregistered apprentice treatment group, we estimated propensity scores on this limited sample using each of the eight covariate combinations from table A.4. We then selected the covariate combination for the comparison group.

TABLE A.4

Selected Models for Treatment and Comparison Group Combinations

Treatment group	Comparison group	Regression model	Covariate set	Sample
Registered	Wagner-Peyser	Double selection LASSO	2	Full sample
Registered	Community colleges	Double selection LASSO	2	Full sample
Unregistered	Wagner-Peyser	Double selection LASSO	7	Remove UI and outlier earnings
Unregistered	Community colleges	Double selection LASSO	6	Full sample

Note: A sample labeled as "remove UI and outlier earnings" indicates that both the treatment and comparison groups were limited to individuals who did not receive UI payments in either the quarter prior to enrollment or the quarter of enrollment, and who did not have pre-treatment earnings that exceed the control group maximum within the period and county.

Model selection. To choose between the potential sets of covariates and the samples for the Wagner-Peyser and community college comparison groups, we used a linear probability model to estimate a prognostic score for the comparison group identified by each set of covariates. The prognostic score is a measure of predicted outcomes based on covariates (Stuart 2010). We estimated the prognostic score using employment in the ninth quarter following enrollment. We then applied prognostic score model predictions to the treatment group to estimate their predicted outcomes. This allowed us to compare average values to identify the treatment and comparison group pair which is most similar. For each treatment group (registered apprentices and unregistered apprentices) and comparison group (Wagner-Peyser participants and community college students) combination, we chose the model (defined as a set of covariates and sample) which produced the closest balance on prognostic score.

Finally, to generate IPWs, we set weights equal to one for all apprentices and equal to $\hat{p}_i/(1-\hat{p}_i)$ for the comparison group, where $\hat{p}_i$ is the estimated propensity score. To create final IPWs, we adjusted the weights such that the sum of all weights was equal for the treatment and comparison groups in each county and quarter-of-entry bin. We dropped treatment and comparison group members in bins with fewer than 5 comparison group members, to avoid giving comparison group members large weights.

Sensitivities. To assess the impact of the sample selection on results for the Wagner-Peyser analyses, we ran a sensitivity analysis using the limited sample for registered apprentices and a sensitivity using the full sample for unregistered apprentices. We did not find any substantive changes to the primary impacts. We also estimated impacts for each treatment—comparison group combination on the alternative set of covariates and found that these changes did not meaningfully change the takeaways.

Sample Balance

Using the double-selection LASSO method, which was selected as the primary approach, we created four sets of treatment and comparison groups for the impact study. We then used the IPWs to weight the comparison samples to resemble the treatment groups more closely. Tables A.5–A.8 present the characteristics of the samples for each of our four comparisons: (1) registered apprentices and Wagner-Peyser participants, (2) registered apprentices and community college students, (3) unregistered apprentices and Wagner-Peyser participants, and (4) unregistered apprentices and community college students. We present the differences in standardized means for each of the individual demographic characteristics. We followed research guidelines in interpreting effect sizes of less than 0.25 in absolute value as indicating sufficient balance for establishing baseline equivalence and effect sizes of less than 0.05 in absolute value as indicating very strong balance.[35]

[35] The Clearinghouse for Labor Evaluation and Research Causal Evidence Guidelines (2022) asserts that, if effect sizes exceed 0.05 and are statistically significant, regression analysis should control for the corresponding variable. The What Works Clearinghouse (2022) stipulates that baseline equivalence can be established, provided that absolute effect sizes are lower than 0.25 standard deviations. Effect sizes exceeding 0.25 standard deviations are considered to indicate poor balance, and studies with such imbalance do not meet evidence standards for quasi-experimental research designs according to the What Works Clearinghouse.

TABLE A.5

Characteristics of the Impact Study Samples: Registered Apprentices Relative to Wagner-Peyser Participants

	Apprentices	Wagner-Peyser (weighted)	Difference	Standardized mean difference	p-value
Sample size	1,271	260,713			
Prognostic score	0.80	0.79	0.01	0.06	0.06
Demographic characteristics					
Female	0.69	0.66	0.03	0.07	0.04
Age					
Less than 18 years	0.00	0.00	0.00	0.02	0.51
18-24 years	0.30	0.30	0.00	0.01	0.88
25-29 years	0.22	0.23	-0.01	-0.02	0.55
30-39 years	0.24	0.23	0.01	0.02	0.51
40-49 years	0.15	0.14	0.01	0.02	0.55
50+ years	0.08	0.09	-0.01	-0.04	0.20
Race					
Race non-Hispanic White	0.57	0.56	0.02	0.03	0.35
Race non-Hispanic Black	0.24	0.26	-0.02	-0.04	0.24
Hispanic	0.10	0.09	0.01	0.03	0.38
Race Asian	0.03	0.04	-0.01	-0.05	0.26
Race mixed/other (incl API)	0.02	0.02	0.00	0.01	0.86
Ex-offender	0.01	0.01	0.00	0.00	0.89
Has a disability	0.04	0.04	-0.01	-0.05	0.21
Veteran	0.06	0.07	-0.01	-0.06	0.10
Low income	0.96	0.96	0.00	0.03	0.33
Pre-enrollment labor market outcomes					
Has four quarters of pre-enrollment earnings data	0.62	0.67	-0.05	-0.10	0.01
Employed prior to enrollment					
Q -1	0.82	0.81	0.01	0.02	0.54
Q -2	0.85	0.83	0.01	0.03	0.38
Q -3	0.80	0.79	0.02	0.04	0.26
Q -4	0.50	0.53	-0.04	-0.07	0.04
Any quarter (Q -4 -Q -1)	0.93	0.92	0.01	0.03	0.39
Earnings prior to enrollment					

	Apprentices	Wagner-Peyser (weighted)	Difference	Standardized mean difference	p-value
Earnings in quarter -1	$8,695	$8,196	$499	0.07	0.04
Earnings in quarter -2	$9,388	$8,796	$592	0.08	0.02
Earnings in quarter -3	$8,602	$8,003	$599	0.08	0.02
Earnings in quarter -4	$4,888	$5,066	-$178	-0.03	0.44
Received UI benefits					
Q -1	0.07	0.08	-0.01	-0.05	0.10
Q -2	0.06	0.05	0.00	0.01	0.70
Q -3	0.05	0.05	0.00	0.00	0.88
Q -4	0.04	0.04	0.00	-0.02	0.57
More than one employer					
Q -1	0.14	0.14	-0.01	-0.02	0.56
Q -2	0.16	0.16	0.00	-0.01	0.76
Q -3	0.14	0.14	0.00	0.00	0.98
Q -4	0.08	0.09	-0.01	-0.03	0.38

Source: NDNH data matched to WIPS data.

Notes: Employment is defined as having any earnings in a given quarter. NDNH = National Directory of New Hires; Q = quarter; WIPS = Workforce Integrated Performance System. Apprentice mean is unweighted; Wagner-Peyser mean is the difference between the apprentice mean and the coefficient from a weighted least squares regression in which the outcome is the characteristic in the table row, where apprentices receive a weight of one and the Wagner-Peyser participants' weights are described in detail in the appendix. Percentages may not sum to 100 due to rounding or missing data.

TABLE A.6

Characteristics of the Impact Study Samples: Registered Apprentices Relative to Community College Students

	Apprentices	Community college (weighted)	Difference	Standardized mean difference	p-value
Sample size	1,124	4,360			
Prognostic score	0.79	0.80	-0.01	-0.06	0.26
Demographic characteristics					
Female	0.44	0.44	0.00	0.00	0.97
Age					
Less than 18 years	0.00	0.00	0.00	0.02	0.85
18-24 years	0.37	0.36	0.01	0.02	0.72
25-29 years	0.25	0.24	0.01	0.03	0.61
30-39 years	0.24	0.25	-0.02	-0.04	0.53
40-49 years	0.10	0.11	-0.02	-0.05	0.36
50+ years	0.05	0.04	0.01	0.05	0.24

	Apprentices	Community college (weighted)	Difference	Standardized mean difference	p-value
Race					
Race non-Hispanic White	0.38	0.35	0.03	0.06	0.27
Race non-Hispanic Black	0.35	0.34	0.01	0.03	0.63
Hispanic	0.09	0.14	-0.05	-0.18	0.02
Race Asian	0.06	0.05	0.01	0.03	0.47
Race mixed/other (incl API)	0.00	0.02	-0.02	-0.27	0.01
Has a disability	0.02	0.00	0.02	0.12	0.00
Pre-enrollment labor market outcomes					
Has four quarters of pre-enrollment earnings data	0.83	0.83	0.00	-0.01	0.86
Employed prior to enrollment					
Q -1	0.76	0.75	0.01	0.02	0.67
Q -2	0.74	0.76	-0.01	-0.03	0.58
Q -3	0.75	0.76	-0.01	-0.03	0.54
Q -4	0.60	0.61	-0.01	-0.02	0.63
Any quarter (Q -4 -Q -1)	0.87	0.86	0.01	0.02	0.62
Earnings prior to enrollment					
Earnings in quarter -1	$6,694	$7,195	-$501	-0.07	0.23
Earnings in quarter -2	$6,667	$6,970	-$303	-0.05	0.41
Earnings in quarter -3	$6,129	$6,459	-$330	-0.05	0.41
Earnings in quarter -4	$4,835	$5,028	-$193	-0.03	0.62
Received UI benefits					
Q -1	0.04	0.03	0.01	0.04	0.41
Q -2	0.05	0.06	-0.01	-0.06	0.30
Q -3	0.07	0.08	-0.01	-0.04	0.47
Q -4	0.07	0.08	-0.01	-0.05	0.44
More than one employer					
Q -1	0.16	0.17	-0.01	-0.02	0.66
Q -2	0.18	0.19	-0.01	-0.02	0.70
Q -3	0.16	0.16	0.00	0.00	0.97
Q -4	0.22	0.21	0.01	0.00	0.93

Source: NDNH data matched to WIPS and community college data.

Notes: Employment is defined as having any earnings in a given quarter. NDNH = National Directory of New Hires; Q = quarter; WIPS = Workforce Integrated Performance System.

TABLE A.7

Characteristics of the Impact Study Samples: Unregistered Apprentices Relative to Wagner-Peyser Participants

	Apprentices	Wagner-Peyser (weighted)	Difference	Standardized mean difference	p-value
Sample size	950	32,642			
Prognostic score	0.79	0.78	0.01	0.09	0.03
Demographic characteristics					
Female	0.80	0.79	0.02	0.04	0.33
Age					
Less than 18 years	0.00	0.00	0.00	-0.03	0.62
18-24 years	0.31	0.32	-0.01	-0.02	0.67
25-29 years	0.16	0.13	0.03	0.07	0.07
30-39 years	0.26	0.24	0.03	0.06	0.16
40-49 years	0.16	0.17	-0.01	-0.03	0.53
50+ years	0.11	0.14	-0.03	-0.11	0.02
Race					
Race non-Hispanic White	0.58	0.57	0.01	0.02	0.64
Race non-Hispanic Black	0.23	0.24	-0.01	-0.02	0.54
Hispanic	0.07	0.04	0.02	0.09	0.02
Race Asian	0.02	0.03	0.00	-0.01	0.88
Race mixed/other (incl API)	0.03	0.03	0.00	0.02	0.70
Ex-offender	0.05	0.05	0.00	0.01	0.81
Has a disability	0.02	0.04	-0.02	-0.13	0.01
Veteran	0.07	0.10	-0.03	-0.10	0.04
Low income	0.87	0.81	0.06	0.18	0.00
Pre-enrollment labor market outcomes					
Has four quarters of pre-enrollment earnings data	0.67	0.70	-0.03	-0.06	0.17
Employed prior to enrollment					
Q -1	0.82	0.82	0.00	0.01	0.80
Q -2	0.82	0.80	0.02	0.05	0.28
Q -3	0.73	0.70	0.02	0.05	0.23
Q -4	0.52	0.55	-0.03	-0.06	0.19
Any quarter (Q -4 -Q -1)	0.91	0.90	0.01	0.03	0.42
Earnings prior to enrollment					
Earnings in quarter -1	$9,210	$8,971	$238	0.03	0.58
Earnings in quarter -2	$9,056	$8,423	$633	0.08	0.11
Earnings in quarter -3	$7,671	$6,998	$673	0.08	0.08
Earnings in quarter -4	$5,012	$5,228	-$216	-0.03	0.53
Received UI benefits					
Q -1	0.00	0.00	0.00	0.00	0.00

	Apprentices	Wagner-Peyser (weighted)	Difference	Standardized mean difference	p-value
Q -2	0.03	0.02	0.00	0.02	0.60
Q -3	0.06	0.05	0.00	0.02	0.63
Q -4	0.04	0.04	0.00	0.01	0.78
More than one employer					
Q -1	0.15	0.18	-0.03	-0.09	0.05
Q -2	0.15	0.16	0.00	0.00	0.92
Q -3	0.14	0.13	0.01	0.02	0.62
Q -4	0.09	0.09	-0.01	-0.02	0.71

Source: NDNH data matched to WIPS data.

Notes: Employment is defined as having any earnings in a given quarter. NDNH = National Directory of New Hires; Q = quarter; WIPS = Workforce Integrated Performance System

TABLE A.8

Characteristics of the Impact Study Samples: Unregistered Apprentices Relative to Community College Students

	Apprentices	Community college (weighted)	Difference	Standardized mean difference	p-value
Sample size	594	3,076			
Prognostic score	0.80	0.80	0.00	0.01	0.90
Demographic characteristics					
Female	0.75	0.79	-0.04	-0.10	0.14
Age					
Less than 18 years	0.01	0.01	0.00	0.01	0.88
18-24 years	0.45	0.48	-0.04	-0.07	0.40
25-29 years	0.13	0.17	-0.05	-0.14	0.33
30-39 years	0.20	0.16	0.04	0.10	0.13
40-49 years	0.14	0.13	0.01	0.01	0.88
50+ years	0.09	0.05	0.04	0.13	0.04
Race					
Race non-Hispanic White	0.49	0.63	-0.14	-0.28	0.00
Race non-Hispanic Black	0.36	0.29	0.07	0.15	0.04
Hispanic	0.04	0.04	0.00	0.00	0.95
Race Asian	0.04	0.02	0.02	0.12	0.01
Race mixed/other (incl API)	0.01	0.02	-0.01	-0.06	0.30
Has a disability	0.00	0.00	0.00	0	0.14
Pre-enrollment labor market outcomes					
Has four quarters of pre-enrollment earnings data	0.92	0.85	0.07	0.26	0.00

	Apprentices	Community college (weighted)	Difference	Standardized mean difference	p-value
Employed prior to enrollment					
Q -1	0.80	0.82	-0.03	-0.06	0.39
Q -2	0.77	0.76	0.01	0.03	0.71
Q -3	0.77	0.78	-0.01	-0.02	0.77
Q -4	0.70	0.66	0.03	0.07	0.34
Any quarter (Q -4 -Q -1)	0.90	0.90	0.00	0.00	1.00
Earnings prior to enrollment					
Earnings in quarter -1	$6,899	$6,832	$67	0.01	0.92
Earnings in quarter -2	$6,711	$6,577	$134	0.02	0.84
Earnings in quarter -3	$6,335	$6,366	-$31	0.00	0.96
Earnings in quarter -4	$5,540	$5,117	$423	0.06	0.44
Received UI benefits					
Q -1	0.02	0.02	0.01	0.04	0.49
Q -2	0.04	0.01	0.03	0.14	0.00
Q -3	0.06	0.02	0.04	0.17	0.00
Q -4	0.06	0.02	0.03	0.14	0.00
More than one employer					
Q -1	0.15	0.18	-0.02	-0.06	0.36
Q -2	0.19	0.15	0.04	0.11	0.09
Q -3	0.18	0.16	0.02	0.05	0.53
Q -4	0.12	0.13	-0.01	-0.02	0.87

Source: NDNH data matched to WIPS and community college data.
Notes: Employment is defined as having any earnings in a given quarter. NDNH = National Directory of New Hires; Q = quarter; WIPS = Workforce Integrated Performance System.

Impact Estimation

We estimated the impacts of participating in an apprenticeship on employment and earnings using linear regression models applying our inverse probability weights. The models included the same covariates that were selected by the LASSO for inclusion in the propensity score model (Exhibit A.3), plus county and quarter of enrollment bin fixed effects. This “doubly robust” strategy ensures unbiased estimates if either the propensity score model or regression model are correctly specified, and it has been found to perform well under a range of circumstances (Busso et al. 2014; Huber et al. 2013). When estimating impacts on earnings we included individuals with zero earnings in the sample. This prevents bias in the estimated impacts on average earnings that would arise from including only employed individuals in the analysis, and results in a consistent sample of individuals across quarters and across the earnings and employment outcomes. Specifically, we estimated the following regression model:

$$y_{ict} = \alpha + \beta T_i + \gamma X_i + \delta_{ct} + \varepsilon_{ict}$$

y_{ict} is the outcome (y) for individual i in county c and who enrolled in their program at time t. T_i is an indicator for whether the individual was an apprentice, X_i is a set of individual covariates, and δ_{ct} is a county—quarter of enrollment fixed effect (that is, an indicator for living in a specific county and enrolling in a program in a specific quarter). ε_{ict} is an individual-specific error term.

Each apprentice in the analytic sample received a weight of one and each comparison group member received a weight, as described earlier in the section, with the comparison group weights for each quarter - country normalized to sum to the number of observations in the treatment group in that quarter and county (Imbens 2015). We use heteroskedasticity-robust standard errors but do not correct for the variance that is introduced from estimation of the propensity score, which may have led to standard errors that were either too big or too small (Abadie and Imbens 2016). However, given the magnitude of the impact estimates relative to standard errors, it is very unlikely that statistical significance would have changed.

To estimate subgroup impacts we replicated this process, restricting the treatment sample to apprentices in the relevant subgroup. For example, to estimate the impact of a health care apprenticeship, we limited the treatment group to apprentices in the health care industry and then reran the process described above.

Detailed Tables for Chapter 5

TABLE A.9

Impact of Registered Apprenticeships on Employment by Quarter, Full Sample Subgroup

	Impacts Relative to Wagner-Peyser			Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
-4	0.00	0.01	0.74	0.50	0.50	1271	0.53	0.50	260713
-3	0.01	0.01	0.24	0.80	0.40	1271	0.79	0.41	260713
-2	0.01	0.01	0.25	0.85	0.36	1271	0.83	0.37	260713
-1	0.01	0.01	0.39	0.82	0.39	1271	0.81	0.39	260713
0	0.11***	0.01	0.00	0.95	0.23	1271	0.83	0.38	260713
1	0.14***	0.01	0.00	0.97	0.18	1271	0.82	0.38	260713
2	0.10***	0.01	0.00	0.95	0.23	1271	0.83	0.37	260713
3	0.08***	0.01	0.00	0.94	0.24	1271	0.85	0.36	260713
4	0.09***	0.01	0.00	0.93	0.26	1271	0.83	0.38	260713
5	0.09***	0.01	0.00	0.93	0.26	1271	0.83	0.37	260713
6	0.07***	0.01	0.00	0.91	0.29	1271	0.83	0.38	260713
7	0.08***	0.01	0.00	0.90	0.30	1211	0.82	0.39	254016
8	0.07***	0.01	0.00	0.89	0.31	1211	0.82	0.39	254016
9	0.08***	0.01	0.00	0.89	0.32	1271	0.80	0.40	260713
-4	-0.02	0.02	0.41	0.60	0.49	1124	0.61	0.49	4360
-3	-0.02	0.02	0.25	0.75	0.44	1124	0.76	0.43	4360
-2	-0.02	0.02	0.33	0.74	0.44	1124	0.76	0.43	4360
-1	0.00	0.02	0.96	0.76	0.43	1124	0.75	0.43	4360
0	0.14***	0.02	0.00	0.87	0.33	1124	0.73	0.45	4360
1	0.18***	0.01	0.00	0.96	0.19	1124	0.78	0.41	4360

	Impacts Relative to Wagner-Peyser			Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
2	0.15***	0.01	0.00	0.94	0.25	1121	0.78	0.41	4358
3	0.15***	0.01	0.00	0.93	0.25	1123	0.78	0.42	4355
4	0.15***	0.01	0.00	0.93	0.25	1124	0.78	0.41	4360
5	0.12***	0.02	0.00	0.92	0.28	1124	0.80	0.40	4360
6	0.12***	0.01	0.00	0.91	0.29	1124	0.80	0.40	4360
7	0.09***	0.01	0.00	0.90	0.30	1124	0.81	0.39	4360
8	0.09***	0.02	0.00	0.88	0.33	1113	0.79	0.41	4161
9	0.09***	0.01	0.00	0.88	0.33	1124	0.80	0.40	4360

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N in ninth quarter= 5,484 (1,124 apprentices and 4,360 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

TABLE A.10

Impact of Registered Apprenticeships on Earnings by Quarter, Full Sample Subgroup

Impacts Relative to Wagner-Peyser				Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
-4	$150	$148	0.31	$4,888	$6,763	1271	$5,066	$6,861	260713
-3	$527	$202	0.01	$8,602	$7,756	1271	$8,003	$7,467	260713
-2	$561	$192	0.00	$9,388	$7,773	1271	$8,796	$7,380	260713
-1	$480	$186	0.01	$8,695	$7,481	1271	$8,196	$7,153	260713
0	$3124***	$129	0.00	$10,813	$6,953	1271	$7,284	$7,151	260713
1	$4,771***	$148	0.00	$12,958	$7,049	1271	$7,836	$7,167	260713
2	$4,495***	$164	0.00	$13,766	$8,426	1271	$8,878	$7,586	260713
3	$3,677***	$170	0.00	$13,418	$7,572	1271	$9,397	$7,749	260713
4	$3,669***	$195	0.00	$13,683	$7,778	1271	$9,670	$8,124	260713
5	$3,449***	$197	0.00	$13,849	$7,836	1271	$10,045	$8,277	260713
6	$4,028***	$207	0.00	$14,648	$9,388	1271	$10,211	$8,468	260713
7	$3,210***	$221	0.00	$13,933	$8,592	1211	$10,267	$8,606	254016
8	$3,213***	$227	0.00	$14,265	$8,886	1211	$10,561	$8,825	254016
9	$3,230***	$236	0.00	$14,305	$9,124	1271	$10,645	$8,922	260713
-4	-309	$263	0.24	$4,835	$5,958	1124	$5,028	$6,352	4360
-3	-478*	$278	0.09	$6,129	$6,204	1124	$6,459	$6,602	4360
-2	-452	$279	0.11	$6,667	$6,431	1124	$6,970	$6,705	4360
-1	-605*	$321	0.06	$6,694	$6,830	1124	$7,195	$7,082	4360
0	$1,838***	$263	0.00	$7,974	$6,627	1124	$6,448	$6,740	4360
1	$5,575***	$218	0.00	$12,879	$6,568	1124	$7,491	$7,207	4360
2	$6,109***	$256	0.00	$13,895	$7,524	1121	$8,038	$7,438	4358
3	$6,199***	$261	0.00	$14,064	$7,894	1123	$8,074	$7,664	4355
4	$5,539***	$276	0.00	$13,696	$7,814	1124	$8,361	$7,922	4360
5	$4,936***	$314	0.00	$13,584	$8,196	1124	$8,976	$8,203	4360
6	$4,892***	$326	0.00	$13,731	$8,471	1124	$9,257	$8,296	4360

	Impacts Relative to Wagner-Peyser			Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
7	$4,366***	$332	0.00	$13,863	$8,732	1124	$9,923	$8,446	4360
8	$4,451***	$332	0.00	$13,525	$8,901	1113	$9,557	$8,657	4161
9	$4,693***	$355	0.00	$13,966	$9,207	1124	$9,801	$8,647	4360

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=261,984 (1,271 apprentices and 260,713 Wagner-Peyser participants). College analysis: N in ninth quarter= 5,484 (1,124 apprentices and 4,360 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

TABLE A.11

Impact of Unregistered Apprenticeships on Employment by Quarter, Full Sample Subgroup

	Impacts Relative to Wagner-Peyser			Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
-4	-0.01	0.01	0.55	0.52	0.50	950	0.55	0.497	32642
-3	0.02	0.02	0.29	0.73	0.45	950	0.70	0.457	32642
-2	0.00	0.01	0.78	0.82	0.39	950	0.80	0.401	32642
-1	-0.01	0.01	0.70	0.82	0.38	950	0.82	0.385	32642
0	0.03***	0.01	0.00	0.88	0.32	950	0.84	0.368	32642
1	0.01	0.01	0.41	0.88	0.33	950	0.86	0.351	32642
2	0.02***	0.01	0.03	0.88	0.32	950	0.85	0.361	32642
3	0.02	0.01	0.14	0.88	0.33	950	0.85	0.359	32642
4	0.03***	0.01	0.01	0.88	0.33	950	0.84	0.371	32642
5	0.05***	0.01	0.00	0.89	0.32	950	0.83	0.380	32642
6	0.04***	0.01	0.00	0.87	0.34	950	0.82	0.387	32642
7	0.04***	0.01	0.00	0.87	0.33	947	0.82	0.387	32257
8	0.05***	0.01	0.00	0.88	0.32	947	0.82	0.386	32257
9	0.05***	0.01	0.00	0.87	0.34	950	0.80	0.400	32642
-4	-0.02	0.03	0.41	0.70	0.46	594	0.66	0.47	3076
-3	-0.01	0.03	0.63	0.77	0.42	594	0.78	0.42	3076
-2	0.02	0.03	0.54	0.77	0.42	594	0.76	0.43	3076
-1	-0.02	0.03	0.55	0.80	0.40	594	0.82	0.38	3076
0	0.10***	0.02	0.00	0.86	0.35	594	0.78	0.41	3076
1	0.17***	0.03	0.00	0.90	0.31	594	0.74	0.44	3076
2	0.16***	0.03	0.00	0.88	0.33	594	0.71	0.45	3075
3	0.09***	0.03	0.00	0.83	0.38	593	0.75	0.43	3071
4	0.10***	0.03	0.00	0.87	0.34	594	0.76	0.43	3076
5	0.10***	0.03	0.00	0.86	0.34	594	0.75	0.43	3076
6	0.10***	0.03	0.00	0.88	0.33	594	0.78	0.41	3076

	Impacts Relative to Wagner-Peyser			Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
7	0.08***	0.02	0.00	0.89	0.32	594	0.80	0.40	3076
8	0.05**	0.02	0.03	0.86	0.35	575	0.83	0.38	2830
9	0.04*	0.02	0.10	0.84	0.37	594	0.81	0.40	3076

Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter= 33,592 (950 apprentices and 32,642 Wagner-Peyser participants). College analysis: N in ninth quarter= 3,670 (594 apprentices and 3,076 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

TABLE A.12

Impact of Unregistered Apprenticeships on Earnings by Quarter, Full Sample Subgroup

	Impacts Relative to Wagner-Peyser			Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
-4	-$46	$251	0.85	$5,012	$7,071	950	$5,228	$7,669	32642
-3	$542	$298	0.07	$7,671	$8,142	950	$6,998	$8,369	32642
-2	$316	$304	0.30	$9,056	$7,844	950	$8,423	$8,472	32642
-1	-$26	$337	0.94	$9,210	$8,053	950	$8,971	$9,003	32642
0	$1,965***	$196	0.00	$10,360	$8,528	950	$8,029	$8,472	32642
1	2,570***	$242	0.00	$11,502	$8,747	950	$8,448	$8,195	32642
2	$2,085***	$234	0.00	$11,521	$8,554	950	$8,873	$7,896	32642
3	$1,650***	$255	0.00	$11,682	$8,513	950	$9,548	$8,512	32642
4	$2,175***	$273	0.00	$12,752	$9,299	950	$10,029	$8,709	32642
5	$1,958***	$280	0.00	$12,615	$8,940	950	$10,122	$8,832	32642
6	$2,719***	$285	0.00	$13,527	$10,104	950	$10,176	$8,621	32642
7	$3,101***	$302	0.00	$14,000	$9,680	947	$10,365	$8,931	32257
8	$3,871***	$317	0.00	$15,062	$10,153	947	$10,560	$8,919	32257
9	$3,368***	$318	0.00	$14,395	$10,135	950	$10,413	$9,194	32642
	Impacts Relative to Community Colleges			Treatment			Comparison		
Quarter	Coefficient	Standard Error	p-value	Mean	Standard Deviation	N	Mean	Standard Deviation	N
-4	-$146	$424	0.73	$5,540	$7,180	594	$5,117	$7,226	3076
-3	-$19	$473	0.97	$6,335	$7,782	594	$6,366	$7,895	3076
-2	$155	$475	0.74	$6,711	$7,857	594	$6,577	$7,961	3076
-1	$205	$474	0.67	$6,899	$8,319	594	$6,832	$8,093	3076
0	$1,474***	$218	0.00	$7,286	$7,790	594	$6,029	$7,323	3076
1	$3,014***	$336	0.00	$9,002	$7,755	594	$6,292	$6,787	3076
2	$2,732***	$412	0.00	$9,404	$8,239	594	$6,938	$7,563	3075

3	$2,077***	$410	0.00	$9,370	$8,572	593	$7,483	$8,087	3071
4	$2,419***	$395	0.00	$9,787	$8,734	594	$7,488	$8,260	3076
5	$2,847***	$444	0.00	$10,088	$8,758	594	$7,421	$7,971	3076
6	$2,712***	$429	0.00	$10,933	$9,217	594	$8,431	$8,161	3076
7	$4,190***	$455	0.00	$12,776	$9,939	594	$8,564	$8,114	3076
8	$4,127***	$562	0.00	$12,899	$10,629	575	$9,840	$8,642	2830
9	$3,490***	$536	0.00	$12,680	$10,324	594	$9,462	$8,711	3076

Source: National Directory of New Hires data matched to Workforce Integrated Performance System (WIPS) and community college data. Data cover participants who enroll 2021Q3—2022Q2 for the Wagner-Peyser analysis and 2022Q1—2022Q2 for the College analysis.
Notes: Employment is defined as having any earnings in a quarter recorded in the National Directory of New Hires. Sample sizes vary slightly quarter-to-quarter. Wagner-Peyser analysis: N in ninth quarter=33,592 (950 apprentices and 32,642 Wagner-Peyser participants). College analysis: N in ninth quarter= 3,670 (594 apprentices and 3,076 community college students).

Statistical significance levels are indicated as follows: *** = 1 percent; ** = 5 percent; * = 10 percent.

References

Abadie, Alberto, and Guido W. Imbens. 2016. "Matching on the Estimated Propensity Score." *Econometrica* 84 (2): 781–807. https://doi.org/10.3982/ECTA11293.

Abraham, Katharine G., John C. Haltiwanger, Kristin Sandusky, and James R. Spletzer. 2018. *Measuring the Gig Economy: Current Knowledge and Open Issues*. Working Paper no. w24950. Cambridge, MA: National Bureau of Economic Research.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen. 2014. "High-Dimensional Methods and Inference on Structural and Treatment Effects." *Journal of Economic Perspectives* 28(2): 1-23.

Blakemore, Arthur E., Paul L. Burgess, Stuart A. Low, and Robert S. St. Louis. 1996. "Employer Tax Evasion in the Unemployment Insurance Program." *Journal of Labor Economics* 14 (2): 210–30.

Busso, Matias, John DiNardo, and Justin McCrary. 2014. "New Evidence on the Finite Sample Properties of Propensity Score Reweighting and Matching Estimators." *The Review of Economics and Statistics* 96(5): 885-897.

Clearinghouse for Labor Evaluation and Research. 2022. "Causal Evidence Guidelines, Version 2.2." Washington, DC: U.S. Department of Labor.

Community College Research Center. 2021. "An Introduction to Community Colleges and Their Students." https://ccrc.tc.columbia.edu/publications/introduction-community-colleges-students.html. Accessed July 9, 2025.

Czajka, John L., Ankita Patnaik, and Marian Negoita. 2018. *Data on Earnings: A Review of Resources for Research*. Report for the U.S. Department of Labor. Oakland, CA: Mathematica Policy Research.

Dula, Christopher. 2021. *The 2021 Net Impact and Cost-Benefit Evaluation of Washington State's Workforce Development Programs*. Washington Workforce Training & Education Coordinating Board.

Employment and Training Administration. n.da. "WIOA Fact Sheet: One-Stop Career Centers." https://www.dol.gov/sites/dolgov/files/ETA/wioa/pdfs/AJC%20Overview%202021_Refugee%20Resettlement_Final.pdf. Accessed July 9, 2025.

Employment and Training Administration. n.db. "Wagner-Peyser Act Employment Service Results." https://www.dol.gov/agencies/eta/performance/results/wagner-peyser. Accessed July 9, 2025.

Gardiner, Karen, Daniel Kuehn, Elizabeth Copson, and Andrew Clarkwest. 2021. "Expanding Registered Apprenticeship in the United States: Description of American Apprenticeship Initiative Grantees and Their Programs." Prepared for the U.S. Department of Labor, Employment and Training Administration. Rockville, MD: Abt Associates; and Washington, DC: Urban Institute.

Gardiner, Karen, Daniel Kuehn, Pamela Loprest, and Stephanie Petrov. Forthcoming. *Scaling Apprenticeship and Closing the Skills Gap Implementation Study Apprenticeship Evidence-Building Portfolio*. Prepared for the U.S. Department of Labor. Washington, DC: Urban Institute.

Glazerman, Steven, Dan M. Levy, and David Myers. 2003. "Nonexperimental Versus Experimental Estimates of Earnings Impacts." *The Annals of the American Academy of Political and Social Science* 589: 63–93. https://doi.org/10.1177/0002716203254879.

Heckman, James J., Hidehiko Ichimura, and Petra E. Todd. 1997. "Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme." *The Review of Economic Studies* 64 (4): 605–54. https://doi.org/10.2307/2971733.

Heckman, James, Hidehiko Ichimura, Jeffrey Smith, and Petra Todd. 1998. "Characterizing Selection Bias Using Experimental Data." *Econometrica* 66 (5): 1017–98. https://doi.org/10.2307/2999630.

Horvitz, Daniel G., and Donovan J. Thompson. 1952. "A Generalization of Sampling without Replacement from a Finite Universe." *Journal of the American Statistical Association* 47 (260): 663–85. https://doi.org/10.1080/01621459.1952.10483446.

Hollenbeck, Kevin, and Wei-Jang Huang. 2003. *Net Impact and Benefit-Cost Estimates of the Workforce Development System in Washington State.* Upjohn Institute Technical Report No. 03-018. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/tr03-018

Hollenbeck, Kevin, and Wei-Jang Huang. 2006. *Net Impact and Benefit-Cost Estimates of the Workforce Development System in Washington State.* Upjohn Institute Technical Report No. 06-020. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/tr06-020

Hollenbeck, Kevin, and Wei-Jang Huang. 2016. *Net Impact and Benefit-Cost Estimates of the Workforce Development System in Washington State.* Upjohn Institute Technical Report No. 16-033. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/tr16-033

Hotz, Joseph V., and John K. Scholz. 2001. *Measuring Employment and Income for Low-Income Populations with Administrative and Survey Data*. Madison, WI: University of Wisconsin–Madison Institute for Research on Poverty.

Houseman, Susan N. 2001. "Why Employers Use Flexible Staffing Arrangements: Evidence from an Establishment Survey." *Industrial and Labor Relations Review* 55 (1): 149–70. https://doi.org/10.2307/2696191.

Huber, Martin, Michael Lechner, and Conny Wunsch. 2013. "The Performance of Estimators Based on the Propensity Score." *Journal of Econometrics* 175(1): 1-21.

Imbens, Guido W. 2004. "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review." *The Review of Economics and Statistics* 86 (1): 4–29. https://doi.org/10.1162/003465304323023651.

Imbens, Guido W. 2015. "Matching Methods in Practice: Three Examples." *The Journal of Human Resources* 50 (2): 373–419. https://doi.org/10.3368/jhr.50.2.373.

Jacoby, Tamar and Ron Haskins. 2020. *Fulfilling the Promise of Apprenticeship*. Washington, DC: Opportunity America and Brookings Institution.

Katz, Lawrence F., and Alan B. Krueger. 2016. *The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015*. Working Paper no. w22667. Cambridge, MA: National Bureau of Economic Research.

Katz, Lawrence F., and Alan B. Krueger. 2019. *Understanding Trends in Alternative Work Arrangements in the United States*. Working Paper no. w25425. Cambridge, MA: National Bureau of Economic Research.

Katz, Batia, Robert Lerman, Daniel Kuehn, and Jessica Shakesprere. 2022. *Did Apprentices Achieve Faster Earnings Growth Than Comparable Workers?: Findings from the American Apprenticeship Initiative Evaluation*. Report prepared for the U.S. Department of Labor, Employment and Training Administration. Rockville, MD: Abt Associates; and Washington, DC: Urban Institute.

Kornfeld, Robert, and Howard S. Bloom. 1999. "Measuring Program Impacts on Earnings and Employment: Do Unemployment Insurance Wage Reports from Employers Agree with Surveys of Individuals?" *Journal of Labor Economics* 17 (1): 168–97. https://doi.org/10.1086/209917.

Kuehn , Daniel, and Moriah Macklin. Forthcoming. The Challenges of Using Randomized Controlled Trials to Study Apprenticeship: Evidence from the Scaling Apprenticeship and Closing the Skills Gap Grants. Prepared for the U.S. Department of Labor Chief Evaluation Office. Washington, DC: Urban Institute.

Kuehn, Daniel and Robert Lerman. 2021. Industry-Recognized Apprenticeship Programs Deserve a Chance to Thrive. Urban Wire. https://www.urban.org/urban-wire/industry-recognized-apprenticeship-programs-deserve-chance-thrive.

Lechner, Michael, Ruth Miquel, and Conny Wunsch. 2011. "Long-Run Effects of Public Sector Sponsored Training in West Germany." *Journal of the European Economic Association* 9: 742–84. https://doi.org/10.1111/j.1542-4774.2011.01029.x.

Lerman, Robert, Tamar Jacoby, Deniz Nemli, and John Colborn. 2024. *How Community Colleges Can Help Scale U.S. Apprenticeships: Evidence from the Field*. Washington, DC: Apprenticeships for America.

Office of Policy Development and Research. "PY 2023 Data Book: WIOA and Wagner-Peyser." March 2025. https://www.dol.gov/sites/dolgov/files/ETA/Performance/pdfs/PY2023/Annual/PY%202023%20WIOA%20and%20Wagner-Peyser%20Data%20Book.pdf. Accessed July 9. 2025.

Reed, Debbie, Albert Yung-Hsu Liu, Rebecca Kleinman, Annalisa Mastri, Davin Reed, Samina Sattar and Jessica Ziegler. 2012. *An Effectiveness Assessment and Cost-Benefit Analysis of Registered Apprenticeship in 10 States*. Washington, DC: U.S. Department of Labor.

Rosenbaum, Paul R. 2002. *Observational Studies, 2nd ed*. New York: Springer.

Rosenbaum, Paul R., and Donald B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70 (1): 41–55. https://doi.org/10.2307/2335942.

Ruggiero, Ryan, and Julia Payne. Forthcoming. "Connecting Participants to Apprenticeship: Findings from Two DOL Grant Programs." Washington, DC: U.S. Department of Labor.

Smith, Jeffrey A., and Petra E. Todd. 2005. "Does Matching Overcome LaLonde's Critique of Nonexperimental Estimators?" *Journal of Econometrics* 125: 305–53.

Solomon-Fears, Carmen. 2011. *The National Directory of New Hires*. Washington, DC: Congressional Research Service.

Stuart, Elizabeth A. 2010. "Matching Methods for Causal Inference: A Review and a Look Forward." *Stat Sci* 25(1):1-21.

Schochet, Peter Z. 2008. *Technical Methods Report: Guidelines for Multiple Testing in Impact Evaluations*. Washington, DC: Washington, DC: National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U.S. Department of Education.

What Works Clearinghouse. 2022. What Works Clearinghouse Procedures and Standards Handbook, Version 5.0. U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance (NCEE).

Wilson, Ron and Din, Alexander, 2018. "Understanding and Enhancing the U.S. Department of Housing and Urban Development's ZIP Code Crosswalk Files," Cityscape: A Journal of Policy Development and Research, Volume 20 Number 2, 277–294.

About the Authors

Jonah Deutsch is a principal researcher at Mathematica. Deutsch specializes in behavioral interventions, evaluation design, and quantitative methods to evaluate the impacts of labor and education programs. Deutsch holds a bachelor's degree in political science and government from Wesleyan University and a PhD in public policy from the University of Chicago.

Daniel Kuehn is a principal research associate in the Workforce, Education, and Labor division at the Urban Institute, where his work focuses on registered apprenticeship and workforce development. Kuehn holds a bachelor's degree in economics and sociology from the College of William and Mary, an MPP in labor market policy from George Washington University, and a PhD in economics from American University.

Karen Gardiner is a senior fellow in the Workforce, Education, and Labor division at the Urban Institute, where she directs evaluations of apprenticeships and other workforce training programs, including their implementation and effects on participants and employers. Gardiner holds a bachelor's degree in political science and business economics from the University of California Santa Barbara and an MPP in public policy from the University of Chicago.

Deborah Reed is a principal researcher at Mathematica. Reed is an expert in labor economics with research interests in policies and programs for disadvantaged populations. Reed holds a bachelor's degree in economics and development studies from the University of California, Berkeley, and a PhD in economics from Yale University.

Julia Payne is a research associate in the Work, Education, and Labor division at the Urban Institute. Her research focuses on topics including youth career pathways, apprenticeship, career and technical education, and opportunities to better support families with low income. Payne holds a bachelor's degree in philosophy and an MPP from the University of Virginia.

Moriah Macklin is a research analyst in the Workforce, Education, and Labor division at the Urban Institute, where her work focuses on education, training, and apprenticeship. Macklin holds a bachelor's degree in economics from California State University, Long Beach.

Ariella Spitzer is a senior researcher at Mathematica. Spitzer's research focuses on designing and conducting studies of employment programs and policies serving vulnerable populations. Spitzer holds a bachelor's degree in economics and statistics from Washington University in St. Louis and a PhD in public policy from Harvard University.

Peter Schochet was a senior fellow at Mathematica. Schochet's work focuses on causal inference methodology and conducting field experiments in the education and labor areas. Schochet holds a bachelor's degree in mathematics from Wesleyan University and a PhD in economics from Yale University.

Astrid Harnack-Eber was a researcher at Mathematica. Harnack-Eber's work focuses on designing and leading large-scale studies in education and labor. Harnack-Eber holds a bachelor's degree in economics and a PhD in economics from the Freie Universität Berlin.

Peter Kress is a senior data scientist at Mathematica. Kress's work focuses on combatting inequality by improving social systems with data driven insights. Kress holds a bachelor's degree in physics and economics from the College of William and Mary.

Statement of Independence

500 L'Enfant Plaza SW
Washington, DC 20024

www.urban.org