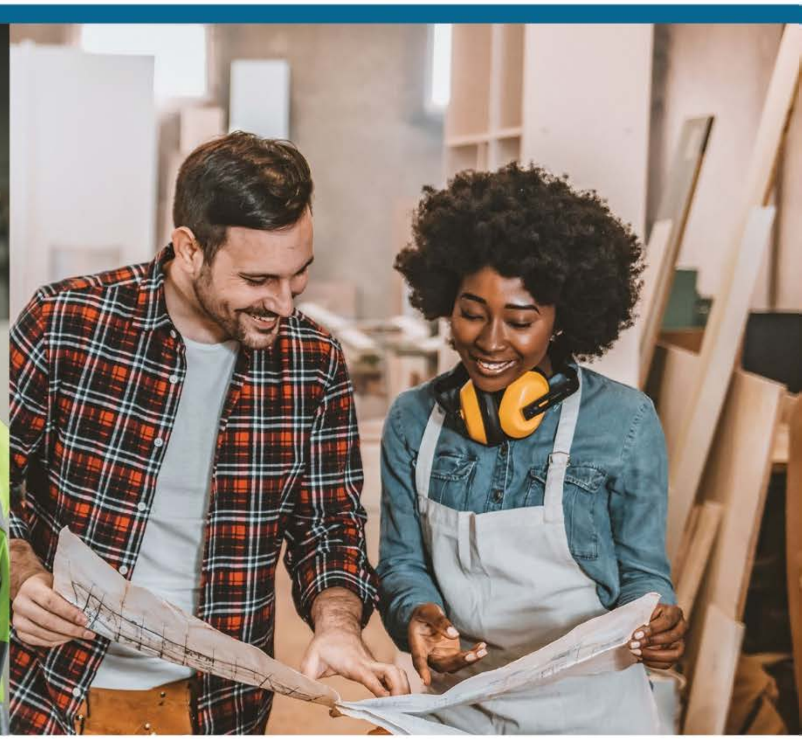
Trade Adjustment Assistance Community College and Career Training Grant Program

Round 4 Early Outcomes Study Report Technical Appendices



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U.S. Department of Labor
Chief Evaluation Office
200 Constitution Avenue, NW
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SUBMITTED BY

Abt Associates
6130 Executive Boulevard
Rockville, MD 20852

IN PARTNERSHIP WITH

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About This Report

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Authors

Douglas Walton
David Judkins
Stas Kolenikov
Marci Schalk
Adrienne Smith

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Abt Associates | 6130 Executive Boulevard | Rockville, MD 20852

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A. Baseline Data

This appendix describes the participant baseline data that were measured at the time of program entry. Section A.1 describes the process by which the baseline data were collected. Section A.2 provides detail on the construction of the measures. Section A.3 discusses the prevalence of missing data and briefly describes the procedure used to multiply-impute missing data.

A.1. DATA COLLECTION PROCESS

The outcomes study enrolled participants from August 2016 through October 2017. This enrollment period captured participants who began their training programs in four cohorts: fall 2016, spring 2017, summer 2017, and fall 2017. Grantees with programs in the outcomes study provided staff who would oversee study enrollment and administer the baseline forms. The baseline forms included an informed consent form and a baseline information form. The research team trained and monitored grantee staff who administered the two forms to participants.

Two site liaisons from the research team were assigned to each of the nine grantees. The site liaisons worked with grant leadership to identify at least one staff person at each participating college or campus to be trained to administer the baseline forms (called the "data collector"). The data collectors were typically program instructors or advisors. Site liaisons developed a data collection manual and training presentation for each grantee and training program. Site liaisons delivered the trainings virtually to grant staff. The manual and training covered all aspects of data collection, including enrollment and consent, content of the baseline information form, human subjects' protections and privacy, data quality, and data security, storage, and transfer to the research team. Data collectors signed Individual Investigator Agreements to indicate they understood their responsibilities to ensure human subjects protections.

The research team established outcome study eligibility requirements. Data collectors ensured that participants were eligible to participate in the study before beginning the data collection process. Across all outcome study programs, potential study participants needed to be at least 18 years old and be enrolled in an outcomes study program (e.g., not auditing the class). In addition, potential participants needed to meet any program-specific eligibility requirements, such as having a valid driver's license for Cincinnati State's CDL program.

Site liaisons worked with grantees to determine at what point in a program study enrollment would occur. In general, the research team and grant staff aimed to enroll program participants the closest time to program start that made sense given program and staff constraints. Enrollment typically occurred on the first day of class or shortly thereafter, in person, as a group, in a classroom or other space on campus. As such, the majority of enrollments occurred at the beginning of each academic semester (including summer terms). A few of the very short-term programs, such as Cincinnati State's CDL program, started more frequently. For these programs, study enrollment occurred more often in order to align with each start of a new training program session.

During study enrollment, data collectors began by describing the study and consenting participants, using scripts and consent forms developed by the research team. Data collectors checked for participant comprehension of consent before asking them to sign two consent form copies (one for participants to retain and one for the research team's records). Data collectors stressed that participation in the study was voluntary and that program participation was not contingent on participating in the study. Grantee-level consent rates are provided in **Exhibit A-1**.

Exhibit A-1. Participant Consents and Declines by Grantee

Grantee	Consents (N)	Declines (N)	Consent Rate (%)
Bossier Parish Community College	60	0	100.0
Chaffey College	544	66	89.2
Cincinnati State Technical and Community College	115	57	66.9
Delgado Community College	454	80	85.0
Ivy Tech Community College	485	252	65.8
Manchester Community College	362	119	75.3
Miami Dade College	265	14	95.0
South Central College	267	40	87.0
Washburn University	215	17	92.7
Total	2,767	645	81.1

Consented individuals then completed the study's baseline information form. They completed a paper version of the baseline information with pen/pencil and were able to ask data collectors questions about the form's content (e.g., to clarify the meaning of a question or word). While data collectors were trained to encourage study participants to answer every item on the baseline information form, they also explained that most items on the form were optional. After participants returned their completed forms to the data collectors, the data collectors reviewed the forms for completeness. Data collectors followed up with participants to address legibility issues or if there were a large number of unanswered items. After study enrollment, data collectors batched the forms by class and program and shipped the materials via FedEx to the research team. To ensure that the data were secure, site liaisons confirmed with grantee staff when each batch of forms was shipped and the number of forms included in each batch.

Site liaisons provided ongoing support to grantee staff during the study enrollment period. Liaisons held planning calls with data collectors before each enrollment cycle to review the process to strategize about ways to improve enrollment rates and data quality, and to identify the specific day and time of baseline form administration. Liaisons also trained new staff members as needed (e.g., following staff turnover) and had debriefing discussions with data collectors at the end of each enrollment cycle. In addition, study leadership monitored enrollment rates and sample sizes over the study enrollment period. The research team identified programs with lower than desired enrollment rates and provided additional support to increase rates in subsequent enrollment cycles.

Once the research team received each FedEx package, they logged the forms, assigning each participant an anonymized unique identifier. The research team built an online data entry system to input data from the baseline information forms. Research assistants and temporary staff, who had been trained in data security procedures, entered the data into the online system. In order to minimize the risk of data entry error, the team entered the data from the forms a second time into a separate database. The research team then manually checked and reconciled any inconsistencies in data entry.

A.2. DETAILS ON BASELINE MEASURES

The research team used data collected from the Baseline Information Form (BIF) to construct a variety of baseline measures. This report uses the baseline measures for several purposes, including: the description of participant characteristics in Chapter 4; definitions of subgroups in Chapter 5; predictors of service receipt in Chapter 6; and predictors of program-specific outcomes in Chapter 7. **Exhibit A-2** describes the definition and construction of the baseline measures.

Exhibit A-2. Description of Baseline Measures

Baseline Measure	Description and Operationalization	Baseline Information Form Items
Age at program entry	Categorical measure of participant age at the time of study enrollment. Derived from date of birth and the date of enrollment into the study. Grouped into four categories (age 20 or less; age 21 to 24; age 25 to 34; age 35 or older).	Question 7 and enrollment date from informed consent form
Sex (male; female)	Binary indicators for whether participant was male or female.	Question 6
Race/ethnicity	Categorical indicator of participant race and ethnicity. Based on two questions: "Are you of Spanish, Hispanic, or Latino origin? "Do you consider yourself to be (select one or more): *1) American Indian or Alaskan Native* *2) Asian* *3) Black or African-American* *4) Native Hawaiian or other Pacific Islander* *5) White"* Responses were grouped into five categories: *1) Hispanic (any race)* *2) White (Non-Hispanic)* *3) Black (Non-Hispanic)* *4) Asian (Non-Hispanic)* *5) Other, including multi-race (Non-Hispanic)*	Questions 9 and 10
Veteran status	Binary indicator for whether the participant had ever been active duty in the military.	Question 16
Living with spouse or partner	Binary indicator for whether the participant was currently married or living with a partner. Based on question "What is your current marital status? *1) Married* *2) Living with partner* *3) Widowed* *4) Divorced/separated* *5) Never married"* Responses 1 and 2 were classified as living with a spouse or partner; responses 3, 4, and 5 were classified as not living with a spouse or partner.	Question 8

<table>
<tr><th>Baseline Measure</th><th>Description and Operationalization</th><th>Baseline Information Form Items</th></tr>
<tr><td>Living with children</td><td>Binary Indicator for whether the participant was living with any of their own children age 17 or younger. Based on question "How many of your children (17 years or younger) currently live in your household?"

Response of 1 or more was classified as living with children; response of 0 was classified as not living with children</td><td>Question 13</td></tr>
<tr><td>Educational attainment</td><td>Categorical indicator of the participant's highest level of education. Based on question "What is the highest degree or level of school you have completed (select only one):
1) No formal education
2) 12th grade or less, no diploma
3) High school graduate
4) GED
5) Technical, trade, or vocational degree
6) Some college credit, but no degree
7) Associate's degree
8) Bachelor's degree
9) Master's degree or higher"

If a respondent selected more than one option, the research team used the highest level. Responses were grouped into six categories:
1) Less than high school (responses 1 and 2)
2) High school or GED (responses 3 and 4)
3) Technical, trade, or vocational degree (response 5)
4) Some college credit, but no degree (response 6)
5) Associate's degree (response 7)
6) Bachelor's degree or higher (response 8)</td><td>Question 17</td></tr>
<tr><td>Employment status</td><td>Categorical indicator of the participant's employment status. Based on question "What is your current employment status?
1) I am currently working at one or more jobs or businesses.
2) I am not currently working, but I have worked at one or more jobs or businesses during the last 12 months.
3) It has been longer than 12 months since I last worked at a job or business.
4) I have never been employed.</td><td>Question 23</td></tr>
</table>

Baseline Measure	Description and Operationalization	Baseline Information Form Items
Current/most recent industry	Categorical indicator of the industry in which the participant was currently or most recently employed. Based on question "Which of the following industries best matches the business of your current/last employer?" Participants could choose among 20 industries, which were aggregated to the following eight categories: *1) Manufacturing* *2) Construction* *3) Transportation and warehousing* *4) Accommodation and Food Services* *5) Retail trade* *6) Health care and social assistance* *7) Professional, scientific, and technical services* *8) Other services* Responses are reported separately for those who were employed at program enrollment, and for those who were not employed but did have some work history.	Question 24
Hourly wage	Continuous variable that measures the hourly wage the participant earned at their current or most recent job. For participants employed at program entry, based on response to question "How much do you earn per hour at your main job, before taxes and other deductions?" For participants not employed at program entry, but who had worked during the past 12 months, based on response to question "When you were working, how much did you earn per hour at your main job?"	Questions 23d and 23f
Expect to be working for pay	Indicator for whether the participant expects to be working for pay in the next few months.	Question 26
Expect to be working full-time or part-time	Indicator for whether the participant expects to be working full-time (35 or more hours per week) or part-time (1 to 34 hours. Based on question "How many hours a week do you expect to be working in the next few months?"	Question 26a
Reason for training	Categorical indicator of primary reason for training. Based on question "What is the most important reason you decided to enroll in this program? *1) Find work* *2) Career change* *3) Career advancement* *4) Educational advancement* *5) Personal reasons* *6) Other"*	Question 27

Baseline Measure	Description and Operationalization	Baseline Information Form Items
Years of experience in target industry	Categorical indicator of years of experience in target industry. Based on question "Please enter the number of years' (and/or months') experience you have in the industry for which you are applying for training." Responses were classified into three categories: 1) *No experience (0 months and 0 years)* 2) *Less than 1 year of experience (1 to 11 months)* 3) *One year or more (12 months or more, or 1 year or more)*	Question 28
Family income	Categorical indicator of family income. Based on question "Please mark that best matches your total family income over the last 12 months, including earnings, pensions, public assistance, alimony, child support, Veteran's payments, etc., before deductions for taxes, bonds, dues, or other items. 1) *$0* 2) *$1-$9,999* 3) *$10,000-$14,999* 4) *$15,000-$19,999* 5) *$20,000-$29,999* 6) *$30,000 or over"* Responses were grouped into three categories: 1) *Less than $15,000 (responses 1, 2, and 3)* 2) *$15,000 to $29,999 (responses 4 and 5)* 3) *$30,000 or more (response 6)*	Question 25
Number of people in household	Continuous measure of the number of people in household. Based on questions "How many of your children (17 years or younger) currently live in your household?" and "Not including yourself, how many adults (18 years or older) currently live in your household?" Used in the construction of the poverty measure.	Questions 13 and 14
Poverty status	Indicator for whether the household was below the federal poverty level. Constructed from exact family income and number of people in household, using 2017 federal poverty guidelines (https://aspe.hhs.gov/2017-poverty-guidelines). For example, the poverty level for a family of three was $20,420. See Section A.3 for discussion of imputation of exact family income.	Questions 13, 14, and 25
Public assistance receipt	Binary indicators for whether the participant was currently receiving benefits from each of the following sources: 1) *Trade Readjustment Allowances (TRA)* 2) *Temporary Assistance for Needy Families (TANF)* 3) *Supplemental Nutrition Assistance Program (SNAP)* 4) *Unemployment Insurance*	Questions 19, 20, 21, and 22

A.3. IMPUTATION OF MISSING BASELINE MEASURES

As is typical in any survey data collection, some participants did not respond to certain questions on the BIF form. As shown in **Exhibit A-3**, item nonresponse ranged from less than 5 percent for demographic characteristics to over 15 percent for questions related to employment, earnings, and income.

Exhibit A-3. Missing Data Rates for Baseline Measures Prior to Imputation

Baseline Measure	Missing Data Rate (%)
Age at program entry	2.2
Sex	3.1
Ethnicity	3.4
Race	4.4
Veteran Status	4.3
Living with spouse or partner	3.5
Living with children	4.4
Educational attainment	4.3
Number of children in household	4.4
Number of adults in household	5.5
Employment status	12.0
Current/most recent industry	15.6
Hourly wage	14.2
Expect to be working for pay	11.0
Expect to be working full-time or part-time	15.1
Reason for training	8.9
Years of experience in target industry	10.2
Family income (categorical)	15.8
Poverty status	16.2
Trade Readjustment Allowances (TRA) receipt	5.1
Temporary Assistance for Needy Families (TANF) receipt	5.3
Supplemental Nutrition Assistance Program (SNAP) receipt	4.8
Unemployment Insurance receipt	4.7

Source: Baseline Information Form
Note: Sample includes all study participants (N = 2,767)

The research team used multiple imputation (Rubin 1987, 1996) to address this item nonresponse. In order to include information from both the BIF and follow-up survey in the imputation models, a set of core baseline and follow-up survey outcomes were imputed jointly. Since both baseline and follow-up survey variables were imputed together imputation model, and the procedure was similar for the two types of data, the full discussion of the multiple imputation appears in Appendix B.3, after the discussion of follow-up survey measures.

A.4. INFERENCES ABOUT THE PARTICIPANTS FOR PROGRAMS LIKE THOSE FUNDED BY TAACCCT

The 34 programs studied in this report served a particular set of participants, but the profile of the student body varied considerably across the programs. If there were another round of TAACCCT grants, the potential participants would doubtless differ in many respects. Much would depend on the labor market at the time. As the novel coronavirus pandemic of 2020 has demonstrated, labor market conditions can change very quickly. The programs in this study were operating near the end of an extraordinarily long expansion that, despite near record low unemployment, had left positions in some industries, such as advanced manufacturing, healthcare, and IT unfilled. Additionally, the nature of the economy necessitates that some workers need to be retrained. Once the pandemic has passed and the people who are most easily employed are back at work, the nation will eventually reach the point again at which there is general prosperity but pockets of people face chronic unemployment or underemployment unless they are re-trained. Future program or grant planners may find it useful to have some idea of what types of participants would avail themselves of the new prorgams at that future time. While that future planner could simply take the observed averages from this study, they would be better served to consider the condidence intervals presented in **Exhibit G.1** of Appendix G.

For example, this study found that 59.5 percent of participants expected at study intake to enroll full time. However, this percentage varied widely across programs. As a result, the 95 percent confidence interval on this percentage runs from 48.4 to 70.6 percent. This confidence interval is strictly valid only if the 34 programs can be viewed as a simple random sample the universe of programs that could be funded in the future. While this assumption is clearly not tenable, future planners would almost certainly do a better job of planning if they planned for a full-time enrollment rate between 50 and 70 percent, rather than assuming either (1) that it would be exactly 59.5 percent again or (2) that all values between 0 and 100 percent are equally plausible.

The confidence intervals of Section G.1 were calculated using the SAS procedure SURVEYMEANS with an adjustment for multiple imputation calculated with another SAS procedure, MIANALYZE. With SURVEYMEANS, the team estimated the "full-sample" variance for a single one of the multiple imputations. It was run with CLUSTER=PROGRAM specification of SURVEYMEANS so as to reflect the extra uncertainty caused by the clustered nature of the sample. The nonresponse weights were also used. Let the variance estimated by SURVEYMEANS for the r-th imputed dataset be denoted as $Q_{g(r)}$ and let the corresponding mean (based on that imputation) be $I_{g(r)}$. With MIANALYZE, the cross-imputation variance was calculated as:

$$U_g = \frac{1}{4}\sum_{r=1}^{5}\left(I_{g(r)} - \overline{I}_g\right)^2 ,$$

where $\overline{I}_g$ is the average estimated mean across the five multiple imputations.

Finally, the total variance of the estimated mean (such as the mean proportion of students expecting to study full-time) is computed using the Rubin's rules to combine the within- and between-imputation variances and produce a consistent estimate of the overall variance:

$$V_g = \frac{1}{5}\sum_{r=1}^{5} Q_{g(r)} + \frac{6}{5}U_g .$$

B. Follow-up Survey Data

This appendix describes the 12-month follow-up survey data collected from study participants. Section B.1 describes the data collection process. Section B.2 provides detail on the construction of the outcomes from the survey data. Section B.3 discusses the prevalence of item nonresponse and the procedure used to multiply-impute missing data. Section B.4 describes the study's approach to survey nonresponse.

B.1. DATA COLLECTION PROCESS

The 12-month follow-up survey was trimodal: participants first had the opportunity to complete the survey via web, followed by phone, and then in-person. The research team administered the survey to 2,211 of the 2,767 study participants, yielding an 80 percent response rate. Survey administration occurred between September 28, 2017 and April 1, 2019 in both English and Spanish.

After participants enrolled in the study, the research team stayed in contact with them to keep contact information updated and thus to increase the likelihood that they would receive and complete the follow-up survey. First, participants received via mail a package welcoming them to the study shortly after program entry. Participants then received tracking emails approximately three and six months after program entry and a tracking letter approximately nine months after program entry. Approximately 12 months after program entry, participants received a prenotification letter and email telling them that survey administration was imminent and that they could complete the survey online.

The survey collected information on training receipt, perceived training quality, and educational progress; training-related supports; employment characteristics; and income and public assistance benefits receipt.[1] Most of the questions came from previous data collection efforts conducted by Abt Associates, such as the short-term and three-year follow up surveys for the first round of the Health Profession Opportunity Grants (HPOG) Program evaluation (HHS), the Pathways for Advancing Careers and Education (PACE) evaluation (HHS), the Green Jobs and Health Care impact survey (DOL), and the Job Search Assistance Strategies impact survey (HHS). The research team pretested the questionnaire in November 2016 on a convenience sample of nine participants who had enrolled in Information Technology programs at Ivy Tech College in fall 2015. Once the questionnaire was finalized, the research team programmed it in ConfirmIt for Computer Aided Web Interviewing and Computer Aided Personal Interviewing administration.

As described in Appendix A, the sample was recruited in four cohorts, which corresponded to the start of each academic term: fall 2016, spring 2017, summer 2017, and fall 2017. **Exhibit B-1** shows the launch and closing dates of the follow-up survey by cohort. For each cohort, the survey was launched approximately one year after enrollment into the study.

Exhibit B-1. Follow-up Survey Launch and Closing Dates by Cohort

Cohort Recruitment Term	Survey Launch Date	Survey Closing Date
Fall 2016	September 2017	June 2018
Spring 2017	March 2018	January 2019

[1] The questionnaire is available from the authors upon request.

Summer 2017	June 2018	March 2019
Fall 2017	September 2018	April 2019

When the survey launched for each cohort, participants first received an email invitation to complete the web-based survey. The research team emailed participants weekly reminders to complete the survey. After approximately one month of web-based survey administration, field interviewers from the research team began to contact non-respondents by phone. After about one month of telephone interviewing attempts, field interviewers began to visit non-respondents in person. Participants received a $25 Visa debit card as a thank you for completing the survey.

Field interviewers, who conducted both phone and in-person interviews, were trained on survey administration in August 2017. The same training was delivered to interviewers who joined the team at a later date because of staff turnover. For quality assurance purposes, field interviewers recorded their interviews with participants (once participants consented to being recorded). The research team reviewed 10 percent of each field interviewer's audio recordings to confirm that survey protocols were being followed.

Exhibit B-2 summarizes the final disposition of cases for the survey.

Exhibit B-2. Final Survey Dispositions

Disposition	Number of Participants
Enrolled in study	2,767
Completed survey	2,211
Refused or broke off	126
Deceased or incarcerated	15
Ineligible for survey due to insufficient identifying information (no date of birth, SSN, or contact information)	41
Unlocatable, unavailable, or other non-refusal	374

B.2. OUTCOMES BASED ON FOLLOW-UP SURVEY DATA

Exhibit B-3 provides a detailed description of all outcomes created from the follow-up survey.

Exhibit B-3. Description of Follow-up Survey Measures

Survey Measure	Definition	Follow-up Survey Items
Training Duration Outcomes		
Total months of training	Calculated as the number of months between the month of enrollment and either the month the participant finished classes (if not still enrolled at follow-up) or the interview month (if still enrolled at follow-up). For example, someone who enrolled in January and finished classes in March was credited with two months of training.	B1, B2
Full-time equivalent (FTE) months of training	Number of full-time equivalent months enrolled in training, where 12 hours per week or more is considered full-time. Calculated as follows: • *If participant spent 12 or more hours per week in training, then full-time equivalent months of training is equal to total months of training.* • *If participant spent 1 to 11 hours per week in training, then full-time equivalent months of training is equal to (total months of training) x (hours per week in training / 12).*	B1, B2, B8
Completed at least 6 FTE months of training	Binary indicator for whether the participant completed at least 6 FTE months of training	B1, B2, B8
Service Receipt Outcomes		
Ever took a course focusing on study skills, workplace skills, or general life skills	Ever took a course during training that focused on study skills, workplace skills, or general life skills	B16
Ever took life skills course focusing on: career planning	Ever took a course during training that focused a great deal of attention on career planning	B17A
Ever took life skills course focusing on: study skills	Ever took a course during training that focused a great deal of attention on study skills	B17B
Ever took life skills course focusing on: job search	Ever took a course during training that focused a great deal of attention on finding a job or moving to a different job	B17C
Ever took life skills course focusing on: critical thinking and problem solving skills	Ever took a course during training that focused a great deal of attention on critical thinking and problem-solving skills	B17D
Ever took life skills course focusing on: finding help with life problems	Ever took a course during training that focused a great deal of attention on finding help with problems at school, work or home	B17E
Type of life skills course: financial aid for school	Ever took a course during training that focused a great deal of attention on finding and applying for financial aid for school	B17F
Ever took life skills course focusing on: time management	Ever took a course during training that focused a great deal of attention on managing time effectively	B17G
Ever took life skills course focusing on: working in groups	Ever took a course during training that focused a great deal of attention on working in groups	B17H

Survey Measure	Definition	Follow-up Survey Items
Ever took life skills course focusing on: communicating well	Ever took a course during training that focused a great deal of attention on communicating well	B17I
Ever took life skills course focusing on: managing stress and anger	Ever took a course during training that focused a great deal of attention on managing stress and anger	B17J
Ever took life skills course focusing on: staying motivated	Ever took a course during training that focused a great deal of attention on staying motivated	B17K
Ever took life skills course focusing on: acting professionally	Ever took a course during training that focused a great deal of attention on acting professionally	B17L
Ever took life skills course focusing on: managing finances	Ever took a course during training that focused a great deal of attention on managing money and personal finances	B17M
Ever took life skills course focusing on: handling family responsibilities	Ever took a course during training that focused a great deal of attention on handling parenting and other family responsibilities	B17N
Offered a work study job as part of studies	Participant stated that they were offered a work study job as part of their studies.	B18A
Offered clinical experience or practicum as part of studies	Participant stated that they were offered clinical experience or a practicum as part of their studies.	B18B
Offered arranged visits from employer/learning about employers as part of studies	Participant stated that they were offered arranged visits from or to learn about an individual employer as part of their studies.	B18C
Offered class taught by instructors from local employer/class offered on-site at local employer as part of studies	Participant stated that they were offered a class taught by instructors from a local employer as part of their studies.	B18D
Offered an apprenticeship as part of studies	Participant stated that they were offered an apprenticeship as part of their studies.	B18E
Offered an internship as part of studies	Participant stated that they were offered an internship as part of their studies.	B18F
Offered other work experience as part of studies	Participant stated that they were offered other work experience as part of their studies.	B18G
Offered opportunity for work study job or internship	This composite measure indicates whether participants were offered one or more opportunities for a work study job, clinical experience or practicum, apprenticeship, internship, or other work experience as part of their studies. Arranged visits from employers and classes taught by instructors from local employers were not included in this measure.	B18A, B18B, B18E, B18F, B18G
Received academic advising	Participants were asked whether they received academic advising, either through the school or through a referral from the school to another organization	C4A
Received financial aid advising	Participants were asked whether they received financial aid advising, either through the school or through a referral from the school to another organization	C4B
Received career counseling	Participants were asked whether they received career counseling, either through the school or through a referral from the school to another organization	C4C

Survey Measure	Definition	Follow-up Survey Items
Received job search or placement assistance	Participants were asked whether they received job search or placement assistance, either through the school or through a referral from the school to another organization	C4D
Received help creating or editing a resume	Participants were asked whether they received help creating or editing their resume, either through the school or through a referral from the school to another organization	C5A
Received help looking for a job	Participants who reported that they received job search or placement assistance (C4D=1) were asked whether they received help looking for a job, either through the school or through a referral from the school to another organization	C5B
Received help using web-based search engines	Participants who reported that they received job search or placement assistance (C4D=1) were asked whether they received help using web-based job search engines, either through the school or through a referral from the school to another organization	C5C
Received help finding specific job leads	Participants who reported that they received job search or placement assistance (C4D=1) were asked whether they received help finding specific job leads, either through the school or through a referral from the school to another organization	C5D
Received help filling out job applications	Participants who reported that they received job search or placement assistance (C4D=1) were asked whether they received help filling out job applications, either through the school or through a referral from the school to another organization	C5E
Received practicing for job interviews	Participants who reported that they received job search or placement assistance (C4D=1) were asked whether they received help practicing for job interviews, either through the school or through a referral from the school to another organization	C5F
Source of funds for training: own earnings or savings or those of a spouse	Participant reported that their own earnings or savings were used to help pay for program expenses	C1A
Source of funds for training: loans in own name or name of a family member	Participant reported that loans in their or a family member's name were used to help pay for program expenses	C1B
Source of funds for training: a parent or other family member	Participant reported that financial help from a parent or other family member was used to help pay for program expenses	C1C
Source of funds for training: grant from the government	Participant reported that a government grant was used to help pay for program expenses	C1D
Source of funds for training: used TRA benefits to pay for training costs	Participant reported that TRA/TAA benefits were used to help pay for program expenses	C1E
Source of funds for training: Veteran's benefits	Participant reported that Veteran's benefits were used to help pay for program expenses	C1F
Source of funds for training: scholarship	Participant reported that a scholarship was used to help pay for program expenses	C1G
Source of funds for training: financial support from employer	Participant reported that financial support from their employer was used to help pay for program expenses	C1H
Source of funds for training: other funding source	Participant reported that another funding source was used to help pay for program expenses	C1I

Survey Measure	Definition	Follow-up Survey Items
Program satisfaction	Categorical indicator of whether the participant was "very satisfied," "somewhat satisfied," or "not satisfied"	B19
Training Progress Outcomes		
Finished classes	Participant finished the required classes in their program of study	B1
Left without finishing classes	Participant left program without completing the required classes in their program of study	B1
Still enrolled	Participant was still enrolled in the required classes in their program of study at follow-up	B1
Program completion	Participant completed the program and reported receiving one or more industry-recognized certificates, licenses or other credentials as a result of completing the required classes.	B3
Started additional training	Participant completed the program, received a credential, and started an additional training program	B15
Plan to return to college	Participant planned to return to college at some point in the future	B15A, B15B
Number of months until planning to return to college	For participants who planned to return to college, this measures the number of months until they planned to return	B15C
Earned any college credits	Participant earned any college credits as part of their program	B9
Number of college credits	Total college credits earned as part of the program. Excludes credits transferred from other institutions and credits for prior learning	B9A
Employment, Earnings, and Income Outcomes		
Currently employed after finishing/leaving program	Participant currently working at a job for pay after finishing or leaving the program. Missing for those still enrolled in program.	D1
Ever employed after finishing/leaving program	Participant reported any paid work since finishing or leaving the program. Missing for those still enrolled in program.	D1, D2
Ever employed after finishing/leaving program and job was in occupation related to training program	For participants who had any paid work after finishing or leaving the program, measures whether that job was "closely related" to their training program. Missing for those still enrolled in program.	D4
Currently employed after finishing/leaving program and job was in occupation related to training program	For participants who were currently employed after finishing or leaving the program, measures whether that job was "closely related" to their training program. Missing for those still enrolled in program.	D4
Ever employed after completing program and job was in occupation related to training program	For participants who had any paid work after completing the program, measures whether that job was "closely related" to their training program. Missing for those still enrolled in program.	D4
Currently employed after completing program and job was in occupation related to training program	For participants who were currently employed after completing the program, measures whether that job was "closely related" to their training program. Missing for those still enrolled in program.	D4
Currently employed full-time after finishing/leaving program	Participants who were currently employed after finishing or leaving the program and worked at least 35 hours per week. Missing for those still enrolled in program.	D6

Survey Measure	Definition	Follow-up Survey Items
Currently employed part-time after finishing/leaving program	Participants who were currently employed after finishing or leaving the program and worked less than 35 hours per week. Missing for those still enrolled in program.	D6
Underemployed	Indicator for whether participants who were currently working part-time after finishing or leaving the program would have preferred to work full-time. Missing for those still enrolled in program.	D7
Reason for wanting part-time work: child care problems	Participant reported child care problems as the main reason they did not want to work full-time (defined for those working part-time who did not want to work full-time)	D8
Reason for wanting part-time work: other family or personal obligations	Participant reported family or personal obligations (other than child care problems) as the main reason they did not want to work full-time (defined for those working part-time who did not want to work full-time)	D8
Reason for wanting part-time work: health or medical limitations	Participant reported health or medical limitations as the main reason they did not want to work full-time (defined for those working part-time who did not want to work full-time)	D8
Reason for wanting part-time work: retired or Social Security limit on earnings	Participant reported that retirement or social security limit on earning as the main reason they did not want to work full-time (defined for those working part-time who did not want to work full-time)	D8
Reason for wanting part-time work: satisfied with income from part-time hours	Participant reported satisfaction with income from part-time hours as the main reason they did not want to work full-time (defined for those working part-time who did not want to work full-time)	D8
Currently employed in job with health insurance and paid sick days	Participant was currently employed in a job that offered health insurance and paid sick days since finishing or leaving the program. Missing for those still enrolled in program.	D5A, D5D
Currently employed in job with health insurance	Participant was currently employed in a job that offered health insurance after finishing or leaving the program. Missing for those still enrolled in program.	D5A
Currently employed in job with paid vacation	Participant was currently employed in a job that offered paid vacation days after finishing or leaving the program. Missing for those still enrolled in program.	D5B
Currently employed in job with paid holidays	Participant was currently employed in a job that offered paid holidays after finishing or leaving the program. Missing for those still enrolled in program.	D5C
Currently employed in job with paid sick days	Participant was currently employed in a job that offered paid sick days after finishing or leaving the program. Missing for those still enrolled in program.	D5D
Currently employed in job with retirement or pension benefits	Participant was currently employed in a job that offered retirement or pension benefits after finishing or leaving the program. Missing for those still enrolled in program.	D5E
Household receipt of TANF	Anyone in participant's household received income or benefits from TANF (Temporary Assistance for Needy Families) in the prior month	E1
Household receipt of SNAP	Anyone in participant's household received income or benefits from SNAP (Supplemental Nutrition Assistance Program) in the prior month	E2
Household receipt of TRA	Anyone in participant's household received income or benefits from TRA (Trade Readjustment Allowances) in the prior month	E3

Survey Measure	Definition	Follow-up Survey Items
Household receipt of other federal support	Anyone in participant's household received income or benefits from federally funded programs other than TANF, SNAP or TRA in the prior month	E4
Household receipt of any public assistance benefits	This composite measure indicates whether the participant's household received income or benefits from TANF, SNAP, TRA or another federally funded program in the prior month.	E1, E2, E3, E4
Household income	Total household income over the prior 12 months, including "earnings, pensions, public assistance, alimony, child support, Veterans' payments, etc., before deductions for taxes, bonds, dues, or other items." Reported as either a continuous measure (E5) or categorical (E5A), with the following response categories: *1) $0* *2) $1-$9,999* *3) $10,000-$14,999* *4) $15,000-$19,999* *5) $20,000-$29,999* *6) $30,000 or over"* Exact income amounts imputed for those participants who only indicated a category.	E5, E5A
Number of people living in household	Total number of people currently living in the household, including adults and own children	E6, E7
Poverty status	Indicator for whether the household was below the federal poverty level. Constructed from exact family income and number of people in household, using 2017 federal poverty guidelines (https://aspe.hhs.gov/2017-poverty-guidelines). For example, the poverty level for a family of three was $20,420. See Section B.3 for discussion of imputation of exact household income.	E5, E5A, E6, E7

B.3. IMPUTATION OF MISSING FOLLOW-UP MEASURES

Survey respondents had the option to decline to respond to any question on the follow-up survey, so each measure has some amount of missing data. **Exhibit B-4** shows item nonresponse rates for selected follow-up survey measures. Missing rates ranged from about 2 to 4 percent for measures related to service receipt and training outcomes; 3 to 8 percent for questions related to employment and benefits receipt; and over 18 percent for household income.

Exhibit B-4. Missing Data Rates for Selected Follow-up Survey Measures Prior to Imputation

Follow-up Survey Measure	Missing Data Rate (%)
Finished classes / left without finishing classes / still enrolled in classes	1.8
Completed program and received target credential	2.9
Received academic advising	3.0
Received financial aid advising	3.4
Received job search or placement assistance	3.2
Offered opportunity for work study job or internship	3.7
Ever took a course focusing on study skills, workplace skills, or general life skills	2.6
Employed after finishing or leaving program	3.1
Employed after finishing or leaving program in a job closely related to training	4.1
Employed in a job that offers health insurance	5.6
Employed in a job that offers paid sick leave	7.6
Household receipt of any public assistance benefits	5.3
Household income, either exact or categorical	18.2

Source: 12-month follow-up survey.
Note: Sample includes all survey respondents participants (N = 2,211)

B.3.1 APPROACH TO IMPUTATION

As noted, to address item nonresponse in both the baseline and follow-up survey data, the research team used standard multiple imputation procedures (Rubin 1987, 1996). Multiple imputation involves using a regression model to fill in missing values. This is done multiple times (hence "multiple" imputation), resulting in a set of 12 imputed values; the team then averaged across the imputed values to produce a final value and standard error.

The imputation included a mix of iterated chain equations (ICE), also referred to as fully conditional specification (FCS), and univariate imputation (van Buuren 2018). Each variable that has missing values was assigned an imputation regression-like model. For most types of outcomes, a generalized linear model type is applicable. Binary outcomes were imputed using logit models; multinomial outcomes were imputed using multinomial logit models; conditional outcomes were imputed using predictive mean matching based on linear regression models; and interval-valued measures were imputed using interval regression.

In order to include information from both baseline and follow-up survey data in the imputation models, a set of core of demographic variables and follow-up survey outcomes were imputed jointly by FCS. The remaining variables received univariate imputations, conditionally on that core of imputed variables.

B.3.2 VARIABLE BLOCKING

To keep models concise and convergent, variables were imputed in two steps—primary FCS imputation, and secondary marginal imputation.

Primary FCS Imputation

First, a set of key baseline and follow-up measures was jointly imputed. These variables include:

- Baseline measures:
  - Gender
  - Age category
  - Race and ethnicity
  - Marital status
  - Education
  - Citizenship
  - Language spoken at home
  - Family income category
  - Employment history
- Follow-up survey measures:
  - Finished classes
  - Employed in a job related to training (among those not still enrolled in training)
  - Receipt of public assistance benefits
  - Family income

This set of variables was simultaneously imputed using the ICE/FCS approach. All of the variables were cross-utilized in each other's regressions. To control for the local effects, grantee indicator variables were used as predictors in the demographic variable regressions, and program indicator variables were used in the follow-up survey outcome regressions. Also, an indicator variable for whether the programs aimed to train participants for occupations in goods-producing industries (such as manufacturing, HVAC, industrial automation, pre-engineering, machining, or mechatronics) was used in all regressions. Finally, the program length was used as a predictor of completion of classes and post-program income, and some demographic interactions (age by gender, age by race/ethnicity, and gender by age) were used in the demographic variable and income regressions. Thus, each imputation regression had between 20 and 40 predictor variables.

Twelve imputed datasets were created for the full baseline sample. For reporting purposes, the imputed data for the follow-up survey variables were later subset to the appropriate sample of survey respondents.

The type of statistical software used to implement multiple imputation differed due to the availability of software in different computing environments. For analysis of survey-based outcomes in Chapters 4 and 5, the baseline measures and survey outcomes were imputed with Stata 16 statistical software. The analysis of earnings data was run on different analytic platforms (see Appendix C for information on National Directory of New Hires Unemployment Insurance wage data). The analyses underlying Chapter 6 were performed on a DOL SAS server and used the SAS/MI/FCS procedure. For this analysis, only five multiple imputations were used. The analyses underlying Chapter 7 were performed on a DOL R container, and used R version of FCS called MICE (Multivariate Imputation by Chained Equations) to implement multiple imputation.

Secondary Marginal Imputation

Once the set of key baseline and follow-up measures was imputed using the ICE/FCS procedure described in the previous section, all other variables were imputed using marginal regressions. For each missing variable, a regression model of the appropriate type (logit, multinomial logit, ordinal logit, predictive mean matching) was used to create the necessary imputations. Imputations were made conditionally on screener variables where appropriate; these screener variables would have been imputed as needed, as well. For these single equation models, program or grantee indicators were used, as needed.

For very sparse data, models were simplified. For example, to impute the missing industry of the current or previous occupation in the baseline data, a multinomial model with imputation variables and program indicators were used for the most populated industries (manufacturing, retail, food service, construction, health care, transportation) vs. all others combined, using imputed variables and program indicators as predictors. The other remaining smaller industries were imputed unconditionally using the observed prevalence rates, without any attempt to control for demographics or program/grantee effects. In addition, in order to impute detailed race, a model had to be used that only contained gender, marital status, education, and age.

B.3.3 VARIABLE TYPES

The imputation regression model differed by the type of variable (binary, multinomial, continuous, or interval).

Binary and Multinomial Variables

Most variables were binary (0/1), and were imputed using logit models. Multinomial variables with more than two categories were imputed with multinomial logit models. The multinomial set of multinomial variables includes:

- Marital status
- Race
- Employment history (never employed; employed in the past; currently employed at follow-up)
- Housing occupancy status (own; rent; live rent-free)
- Most important motive for enrollment (6 categories: find work, career change, career advancement, education advancement, personal, other)
- Industry of current or former employment

Continuous Variables

The continuous variables included:

- Number of adults in the household at baseline and at follow-up
- Number of children in the household at baseline and at follow-up
- Hourly wage at baseline at current or previous job
- Number of college credits or transfer credits earned
- Actual weeks in training
- Hours per week worked, hours per week in training

Given the irregular distribution of these variables (e.g., college credits spiking at multiples of 3 and 4, with troughs at other values, especially at the higher end of the range), the research team used a predictive mean matching (PMM) method to impute the missing values.

Interval-valued Variables

Interval-valued variables are measures that are reported in intervals. The two such variables in this data are baseline and follow-up household income. At baseline, participants could only provide an interval response ($0; $1 to $9,999; $10,000 to $14,999; $15,000 to $19,999; $20,000 to $29,999; and $30,000 or more). In the follow-up survey, respondents could either provide an exact amount or select one of the intervals.

Interval regression was used to impute exact income from the interval responses, with the income levels specified in the log form. For the analysis of survey outcomes, the Stata MI IMPUTE INTREG command within the ICE specification was used to produce plausible values on the continuous scale of income within the specified range. Categories of income were then derived from the continuous values. To allow imputation of zero incomes, the log specification included an offset, so that the intermediate imputation variable had the form of log(income+offset) where offset was set to $8,000, which approximately corresponds to the 10th percentile of the imputed income distribution.

Conditional Variables

Some variables are only applicable to certain participants based on their responses to previous questions – for example, in the follow-up survey, questions about current employment were only asked of participants who were not still enrolled in their training program. Thus, the screener questions were imputed first, then the conditional variables were imputed for the participants who met the screener condition.

B.3.4 TREATMENT OF THE HIERARCHICAL STRUCTURE OF THE DATA

Standard errors and confidence intervals in Chapters 4, 5, and 6 reflect variability across programs. In order for the variability across programs not to be reduced by imputation, one option would be to only use information from other participants in the same program to impute missing data. However, the sample sizes are too small to make this a practical solution. As a compromise, the research team used program indicators as fixed effect predictors. This approach is known to inflate the variation between groups (van Buuren 2018, sec. 7.3.2), which can be viewed as conservative in the context of this evaluation.[2]

Several small programs have about 15 participants, and about half a dozen programs with 25 to 30 participants. Some of the smaller programs were combined with larger ones to avoid unnecessary losses in degrees of freedom:

- Technology (Ivy Tech: Database Management, n=11; Server Administration, n=24; Informatics, n=25; Computer Science, n=26; Chaffey: Pre-Engineering, n=15)
- Welding Technology (Manchester, n=21; and Washburn, n=27)
- All others (Bossier: Fast Track to Manufacturing, n=19; Miami Dade: TRAMCON Basic, n=13; TRAMCON Advanced, n=10; South Central: Right Skills Now, n =10; Machining, n = 26; Chaffey: Mechanical Craft, n = 25)

B.4. SURVEY NONRESPONSE ANALYSIS

B.4.1 EVIDENCE OF NONRESPONSE BIAS IN UNADJUSTED OUTCOME MEANS

A total of 2,767 adults filled out the BIF and 2,211 of them responded to the follow-up survey, yielding a response rate of 80 percent. To the extent that study participants who responded to the follow-up survey may be different from those who did not, there is a risk that estimates could be subject to nonresponse bias.

We used demographic variables collected on the BIF to predict response to the follow-up survey. Missing information in the predictor variables were categorized into a separate category for purposes of modeling. The PROC GLMSELECT procedure in SAS was used to identify the most significant predictors of response to the follow-up survey. A series of models were run to identify potential predictors, including both Least Absolute Shrinkage and Selection Operator (LASSO) and forward stepwise methods. For both of the two methods, a model was run on the full sample of 2,767 baseline respondents and three additional models were run using the full sample randomly split into a training dataset and a validation dataset. The training datasets contained a random 80 percent of the sample and were used to train the models. The validation datasets contained the remaining 20 percent of the sample and were used to predict survey response. **Exhibit B-5** compares the results of these eight models in terms of the significance of the baseline variables in predicting response to the follow-up survey. The starred predictor variables in the table were selected for use in constructing the nonresponse weights.

2 An alternative approach, as described in Chapter 7 of van Buuren (2018), is to fit a multilevel model to each outcome (with individuals being level-1 units, and programs being level-2 units), generate random draws of parameter values and random effects, and generate imputed values as expected value plus noise (i.e., create posterior draws). While statistically appealing, this modeling approach is not computationally feasible for imputation of hundreds of outcomes. Moreover, some of the commonly used methods, such as predictive mean matching (PMM), arguably the most robust imputation method, do not have a natural multilevel extension.

Exhibit B-5. Significant Predictors of Response to Follow-up Survey by PROC GLMSELECT Model Type

Predictor Variable from Baseline Survey	Forward Stepwise Method				Lasso Method			
	Full Sample	80% Training / 20% Validation			Full Sample	80% Training / 20% Validation		
Industry of most recent employment*	X	X	X	X	Education, Public Admin/Admin	Education, Public Admin/Admin, Construction/Utilities	Education, Manufacturing/Mining, Public Admin/Admin	
Education Level*	X	X		X	Associate's Degree, GED	Associate's Degree, Bachelor's degree, GED	Associate's Degree, Bachelor's degree, Master's degree	Associate's Degree
Home ownership			X			Own	Live rent free	
Hispanic ethnicity								
Race		X					Asian	
Annual family income								
Reason for enrolling	X			X		Career change	Career change	
Marital status*	X	X		X	Living with partner, Married	Living with partner, Married	Living with partner, Married	Living with partner, Married
Military status						No		
US citizen								
Non-English speaker at home		X						
Sex*	X	X	X	X				
Household received public assistance								
Grantee*	X	X	X	X	Manchester	Manchester	Manchester	
Program							HVAC	
Most recent hourly wage (categorical)*	X	X	X		4+ times the minimum wage	4+ times the minimum wage	0-2 times, 3-4 times, 4+ times min wage	
Expected Work Hours (categorical)	X			X				
Years of work experience in industry (categorical)								
Number of adults in household (categorical)*	X	X	X	X	1 adult, 3 adults	1 adult, 3 adults	1 adult, 2 adults, 3 adults	1 adult, 3 adults
Number of children in household (categorical)*	X	X	X	X	3+ children	3+ children	3+ children	

Note: * denotes predictor was selected for use in constructing the nonresponse weights.

B.4.2 CONSTRUCTION OF NONRESPONSE ADJUSTMENT WEIGHTS

The final nonresponse adjustment weight was computed in two steps. First, a response propensity adjustment weight (WEIGHT1) was computed for the 2,767 BIF respondents. The final nonresponse weight (WEIGHT2) was computed for all 2,211 follow-up survey respondents which calibrates the response propensity weight of follow-up survey respondents to characteristics of the BIF respondents.

The PROC LOGISTIC procedure in SAS was used to estimate a logistic regression model in which responding to the follow-up was regressed on eight characteristics measured in the BIF that were selected by the procedure described in the previous section:

- Industry of most recent employment
- Education level
- Marital status
- Sex
- Grantee of the program attended
- Hourly Wage of most recent employment (computed in comparison to minimum wage)
- Number of adults in the household (1, 2, 3, 4+ adults)
- Number of children in their household (0, 1, 2, 3+ children)

The inverse of the raw estimated response propensities from this model were used to compute a response propensity weight (WEIGHT1) for all 2,767 BIF respondents, assigning a value of zero to nonrespondents. As a final step in the weighting, the characteristics of follow-up survey respondents were calibrated to match the distribution of the entire frame of BIF respondents. We used an iterative adjustment called raking[3] that aligned weighted totals of follow-up survey respondents with the baseline distribution on these seven dimensions:

- Industry of most recent employment
- Education level
- Marital status
- Sex
- Grantee of the program attended
- Number of adults in the household (1, 2, 3, 4+ adults)
- Number of children in their household (0, 1, 2, 3+ children)

The final raked nonresponse weight (WEIGHT2) is computed for all follow-up survey respondents (2,211) and scaled to sum to the total number of BIF respondents (2,767). **Exhibit B-6** shows a summary of the nonresponse weights.

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[3] A description of the raking procedure and SAS code is available here: https://www.abtassociates.com/raking-survey-data-aka-sample-balancing

Exhibit B-6. Description of Final Nonresponse Weights

Weight Variable	Sample Size	Min Weight Value	Max Weight Value	Mean Weight Value	Approximate Design Effect
WEIGHT1 Response Propensity Weight	2,211	1.020	2.023	1.251	1.009
WEIGHT2 Final Nonresponse Weight (Follow-up respondents only)	2,211	1.014	2.033	1.251	1.010

B.5. INFERENCES ABOUT MEAN OUTCOMES FOR PROGRAMS LIKE THOSE FUNDED BY TAACCCT

Parallel to the discussion in Section A.4 of Appendix A, **Exhibit G.2** through **G.5** of Appendix G contain confidence intervals for mean outcomes and **Exhibit G.6** through **G.9** of Appendix G contains confidence intervals for differences in mean outcomes across subgroups defined by participant characteristics at program entry. These were calculated using the same methodology discussed in Section A.4. They should help future program and grant designers communicate to future program participants and funders reasonable expectations for the mean outcomes of a new program or a new round of grant-funded programs. The confidence intervals are strictly valid only if the 34 studied programs can be viewed as a simple random sample of a broader universe of programs that could be created by the program designer or funded by future grant-funding mechanism. While this assumption is clearly not tenable, the confidence intervals should still lead to better decision-making than assuming either that the results of this study will be exactly replicated or that nothing at all is known about the likely outcomes. Also, clearly, the confidence intervals will be more useful if the future program is implemented under the same general economic conditions that prevailed in the late 2010s, i.e., late in a multi-year economic expansion.

These confidence intervals were calculated with the aid of two SAS procedures, MIANALYZE for multiple imputation analysis, which in turn called SURVEYMEANS to produce results for each imputation (a set of completed data). The calculations involved corrections for the extra uncertainty introduced by clustering, weighting and imputation. The 34 programs were treated as clusters. Subgroups were treated as domains. The formulas for multiple imputation in Section A.4 also apply here.

C. Unemployment Insurance Wage Data

This appendix describes the Unemployment Insurance (UI) wage data collected for study participants from the National Directory of New Hires (NDNH), a centralized database operated by the federal Department of Health and Human Services Office of Child Support Enforcement (OCSE). The NDNH contains quarterly wage information submitted by state workforce agencies. OCSE also supplements the state reports with records about earnings from federal civilian and military jobs (which are otherwise not covered by state UI data). Section C.1 describes the data collection process. Section C.2 provides detail on the construction of the measures.

C.1. DATA COLLECTION PROCESS

The primary purpose of the NDNH is to assist state child support agencies to locate a non-custodial parent living or working in a different state in order to establish or enforce a child support order. However, subject to federal law and other requirements to protect data privacy and security, OCSE may disclose certain information contained in the NDNH to local, state, or federal agencies for research purposes.

DOL and OCSE negotiated a memorandum of understanding (MOU) allowing access to NDNH data for the TAACCCT evaluation. Among other provisions, the MOU specifies the participant-level data that may be merged with NDNH data and procedures for maintaining the security and confidentiality of the data.

There is a two-step process for collecting NDNH data for research. First, the research team transmitted "match" request files to OCSE. These match request files contain the names and SSNs of study participants. OCSE verifies with the Social Security Administration that the reported SSNs belong to the named persons. For those SSNs that are successfully verified, OCSE copies all earnings records from the NDNH and makes them available for DOL to save in a secure folder. These copied records contain a pseudo-SSN; the records are stripped of all personal identifiers.

The NDNH database only maintains the most recent two years of earnings data, so each match file returns about eight quarters of data. In order to be able to analyze the longest period of data possible, the research team submitted match request files quarterly, beginning in late 2016, when participants first enrolled in the study, and continuing through September 2019.

The second step of the data collection process involves merging study data on to the wage files. The MOU between DOL and OCSE identifies a specific set of baseline and follow-up survey variables that can be merged with the wage files, after OCSE verifies that the variables are formatted according to the approved layout. The research team submitted this "passthrough" file to OCSE. OCSE then strips the personal identifiers out of the passthrough file and replaces the actual SSN with the same pseudo-SSN previously assigned to the archived wage records. The research team then used this pseudo-SSN to merge baseline and follow-up survey data with the quarterly wage data in order to conduct analysis on DOL's secure server.

NDNH earnings data was only available for participants who provided valid names and SSNs in the BIF that could be validated by the Social Security Administration. Like other items on the BIF, SSN was an optional item for participants, and a sizeable number did not provide an SSN. As a result, NDNH earnings data was only available for 2,355 participants who provided a verified name and SSN, or about 85 percent of the full study sample of 2,767.

C.2. DETAILS ON MEASURES

Enrollment into the study began in August 2016 and ended in October 2017. Given the lag of up to six months in processing of employer reports by the states and transfer of state data to OCSE, wage records from NDNH were available through Quarter 1 2019 (March 31, 2019). This provided five quarters of post-enrollment data for everyone in the sample with a verifiable name and SSN, and up to 10 post-enrollment quarters for those enrolled earlier in the period. This report also includes earnings in the quarter of enrollment and the first three pre-enrollment quarters.

Note that pre-enrollment and post-enrollment quarters are defined relative to the calendar quarter of program entry. For example, participants who enrolled between January 1, 2017 and March 31, 2017 were enrolled in Quarter 1 2017, which is designated as their quarter of program entry. For these participants, their fifth post-enrollment quarter is Quarter 2 2018.

Quarterly earnings were calculated by adding up earnings reported across all jobs held in that quarter. Participants were considered to be employed if they had any earnings during the quarter, and not employed if they had zero earnings during the quarter. **Exhibit C-1** contains a description of the NDNH-based earnings and employment measures.

Exhibit C-1. Description of NDNH-based Earnings and Employment Measures

Measure	Definition	Source
Quarterly earnings	Total earnings from all jobs reported during a calendar quarter. Reported for the following quarters: • *3rd quarter before program entry* • *2nd quarter before program entry* • *1st quarter before program entry* • *Quarter of program entry* • *1st quarter after program entry* • *2nd quarter after program entry* • *3rd quarter after program entry* • *4th quarter after program entry* • *5th quarter after program entry* Missing for individuals without a valid name and SSN.	National Directory of New Hires

Measure	Definition	Source
Quarterly employment	Binary indicator for any earnings during a calendar quarter. Reported for the following quarters: • *3rd quarter before program entry* • *2nd quarter before program entry* • *1st quarter before program entry* • *Quarter of program entry* • *1st quarter after program entry* • *2nd quarter after program entry* • *3rd quarter after program entry* • *4th quarter after program entry* • *5th quarter after program entry* Missing for individuals without a valid name and SSN.	National Directory of New Hires
Change in quarterly earnings between the 3rd quarter before program entry to the 5th quarter after program entry	Total earnings in the 5th quarter after program entry minus total earnings in the 3rd quarter prior to program entry. Missing for individuals without a valid name and SSN.	National Directory of New Hires

C.3. IMPUTATION OF MISSING DATA

All analyses of quarterly earnings and employment outcomes used the set of 2,355 participants with complete NDNH data. The research team did not impute any of the NDNH variables, but did impute missing baseline and follow-up survey measures that were used in analysis. They imputed these data in three distinct operations on different platforms: Once on the Abt Associates secure server (ACE3) for Research Questions 4, 5 and 6; once on the DOL SAS server for Research Question 7; and once on a DOL container for RStan for Research Question 8. If the ACE3 imputation had been conducted before creating the passthrough file, this three-fold imputation could have been avoided. However the schedule did not permit this approach. Moreover, the three-fold imputation allowed better customization of the imputation procedures to the research questions. The research team used SAS PROC MI to impute missing baseline subgroups and service receipt outcomes for the analysis in Chapter 6, using the fully conditional specification (FCS) approach described in Appendix B.3. R statistical software was used for imputation of baseline data for the analysis of outcomes by program in Chapter 7, using the Multivariate Imputation by Chained Equations (MICE) package (van Buuren 2018). This imputation used logs of NDNH earnings in Quarters –3, 0 and +5 as variables in the model; Quarter 0 is the natural baseline; Quarter 5 is the natural outcome; and Quarter –3 is used to make the imputation model consistent with the outcome eventually modeled in small area estimation for Chapter 7 (growth in earnings between Quarter –3 and Quarter 5).

D. Service Impacts

This appendix describes procedures used to estimate the impacts of service receipt on outcomes reported in Chapter 6. Section D.1 describes the general methodological approach. Section D.2 provides specific model results for each outcome. Section D.3 discuss the assumptions required for the impacts to be interpreted as causal and potential reasons why those assumptions may not necessarily hold.

D.1. GENERAL METHODOLOGY

The procedure used to estimate the impact of service receipt on outcomes involves calculating regression-adjusted differences between those who received and those who did not receive each particular service. In an attempt to make the process more transparent to readers not acquainted with logistic or linear regression, the team fit these models in a novel manner involving four steps and visual aids. The text below includes a brief summary of the steps, followed by more detail about each.

D.1.1 BRIEF SUMMARY OF STEPS

1. Determine which exogenous factors are relevant to the outcome;
2. Fit a working model for the outcome in terms of only the relevant exogenous factors while ignoring service receipt patterns;
3. Use the working model to calculate the predicted outcome level, separately for those who received each service and those who did not;
4. Calculate the difference between the actual and predicted outcome levels, separately for those who received each service and those who did not. The difference in these differences is the estimated impact of receiving the particular service.

D.1.2 DETAILS ON STEP 1

The team started from a large collection of potentially relevant exogenous factors:

- Age (4 categories)
- Gender
- Race/ethnicity (4 categories)
- Family structure (4 categories)
- Educational attainment at program entry (6 categories)
- Family income at program entry (both a 3-level categorical variable and a continuous variables)
- Housing tenure (3 categories)
- Receipt of Trade Readjustment Allowances at program entry
- Receipt of Supplemental Nutrition Assistance Program (SNAP) benefits at program entry
- Receipt of Temporary Assistance for Needy Families (TANF) benefits at program entry
- Employment status/length of unemployment at program entry (4 categories)

- Primary reason for program enrollment (6 categories)
- Expected work hours during training (4 categories)
- Citizenship
- Veteran status
- Language spoken at home (2 categories, English or non-English)
- Plan for full-time study
- Years of experience in target industry (3 categories)
- Current/last industry (10 categories)
- Family poverty status at program entry
- A binary flag for whether target industry is goods producing (versus services)
- Expected duration of program in months
- County employment rate among the working-age population[4]

Out of a desire to avoid problems of multicollinearity and to simplify the presentation of prediction models, the team first winnowed this long list down to a few critical exogenous factors for each outcome. The team did this separately for each of five outcomes—program completion, training-related employment, change in earnings, public assistance benefit receipt, and poverty.

For this winnowing process, the team used relatively recently developed technique to determine which exogenous factors are relevant to the outcome. The technique is known as "least absolute shrinkage and selection operator" (LASSO) with "10-fold cross-validation."[5] With the LASSO, the sum of absolute values of the estimated regression coefficients in a proposed model is constrained to be less than a preselected value (the "constraint"). If the value for this constraint is small enough, many coefficients in the proposed model will be forced to zero in order to fit within the cap on the sum of absolute coefficient values and thus can be removed from the list of baseline covariates. The 10-fold cross-validation is used to optimize the value of the constraint, rather than just relying on an arbitrary choice for it.

Details of the procedure are as follows:

1. With 10-fold cross-validation, the sample is divided into 10 equal and mutually exclusive random subsamples.
2. For each of a range of candidate values of the constraint, the LASSO procedure is run to select covariates on a sample in which one of the 10 subsamples has been dropped.
3. A linear model is fit on the same sample using just the variables selected in the second step for each of the candidate values of the constraint.

[4] This variable was not available for the earnings analysis.

[5] See Bühlmann and van de Geer (2011) for a full explanation of these techniques.

4. The model is used to create out-of-sample predictions of the outcome for everyone in the dropped piece of the sample, and the prediction error Yˆ_i-Y_i is measured for each of the candidate values of the constraint.
5. Steps 2 through 4 are repeated 10 times for each candidate value of the constraint. On each iteration, a different one of the 10 subsamples is dropped. In this manner, out-of-sample prediction errors are obtained for the entire sample.
6. Mean squared prediction errors across all 10 replicates are then calculated for each of the candidate values of the constraint.
7. The value of the constraint that minimizes this cross-validated mean squared prediction error and thus captures most of the variation reduction possible with the available covariates is selected as the optimal constraint.[6] Whichever variables have nonzero coefficients in the model for that optimal constraint are selected as relevant to the outcome. All other exogenous factors are ignored. All of this is done automatically in SAS®/GLMSELECT.

A couple of technical notes about GLMSELECT. First, it does not support a logistic LASSO, only a linear logistic. This is not a serious problem, but it does mean that some of the selected variables turn out not be to statistically significant in the final logistic regression model. Second, the cross-validated LASSO option in GLMSELECT works on dummy variables created for each level of multi-level categorical variables. It ignores the larger framework surrounding each dummy. This means that, for example, it may select just one of the 10 current/prior industries or just one race/ethnicity level for inclusion in the set of relevant exogenous variables.

Finally, it is worth noting that team repeated the LASSO separately for each of five multiply-imputed datasets. This should capture the extra uncertainty due to winnowing variables based on their imputed values.

D.1.3 DETAILS ON STEP 2

For binary outcomes, the team fit the logistic model in equation C-1. The team did this separately for each of five multiple imputations.

$$\lambda_i = \alpha + X_{1i}\beta_1 + \cdots + X_{pi}\beta_p, \qquad \text{(C-1)}$$

where

i indexes program,

Y_i is a binary outcome indicating whether the person experienced the outcome (completing the program, obtaining training-related employment, having income below the poverty threshold, or receiving public assistance benefits,

[6] One could simply use the LASSO to select covariates with a pre-specified value of the constraint, but the 10-fold cross-validation provides a principled method for selecting the constraint.

$\lambda_i = \log\left[\frac{\Pr\{Y_i = 1\}}{1 - \Pr\{Y_i = 1\}}\right]$ is the logit probability of the person *i* experiencing the outcome,

$X_{1i}, \cdots, X_{pi}$ is a collection of *p* baseline covariates such as race and dummy variables for each program, and

$\alpha, \beta_1, \cdots, \beta_p$ are unknown coefficients to be estimated.

For change in earnings, the team fit the linear model in equation C-2. The team also did this separately for each of five multiple imputations.

$$Y_i = \mu + X_{1i}\gamma_1 + \cdots + X_{pi}\gamma_p + e_i, \tag{C-2}$$

where

Y_i is the change in earnings over the two-year period from three quarters prior to program entry to the fifth quarter following program entry and

e_i is a normally distributed random error.

The team fit models C-1 and C-2 on the total sample, ignoring receipt of services. Therefore, the estimated regression coefficients reflect that average contribution of exogenous factors across observed (but ignored) service-receipt conditions.

D.1.4 DETAILS ON STEP 3

For the binary outcomes, once equation C-1 had been fit, the predicted probability of a person experiencing the outcome was calculated as:

$$U_g = \frac{1}{4}\sum_{r=1}^{5}\left(I_{g(r)} - \overline{I}_g\right)^2,$$

where

g_i indicates whether the person received service g, and

w_i is a nonresponse-adjustment weight.

Similarly, for change in earnings, the "excess increase in earnings" was calculated as

$$B_g = \frac{\sum w_i g_i \left(Y_i - \hat{Y}_i\right)}{\sum w_i g_i}.$$

The impact of receiving the service was then calculated as

$$I_g = B_1 - B_0$$

This same equation was used for both binary outcomes and change in earnings.

The variance on these estimated impacts was calculated using a combination of SAS/SURVEYMEANS and SAS/MIANALYZE.

With SURVEYMEANS, the team estimated the "full-sample" variance for a single one of the multiple imputations. It was run with cluster=program so as to reflect the extra uncertainty caused by the clustered nature of the sample. The nonresponse weights were also used. Let this estimated variance be denoted as $Q_{g(r)}$ and let the corresponding impact (based on that imputation) be $I_{g(r)}$. With MIANALYZE, the cross-imputation variance was calculated as:

$$U_g = \frac{1}{4}\sum_{r=1}^{5}\left(I_{g(r)} - \overline{I}_g\right)^2,$$

where $\overline{I}_g$ is the average estimated impact across the five multiple imputations.

Finally, the total variance of the estimated impact is:

$$V_g = \frac{1}{5}\sum_{r=1}^{5} Q_{g(r)} + \frac{6}{5}U_g.$$

Regarding transparency with a non-technical audience, note that the estimated impact (for either a binary or continuous outcome) should be similar to what would be obtained from a linear model of the form C-3.

$$Y_i = \mu + X_{1i}\gamma_1 + \cdots + X_{pi}\gamma_p + I_g g_i + e_i, \qquad \text{(C-3)}$$

Our hope though is that displaying expected mean outcomes, actual mean outcomes, their differences, and the difference of the difference will give the non-technical reader better insight into the nature of the causal machinery.

D.2. MODEL RESULTS BY OUTCOME

This section displays the working models used for each outcome. There was a slightly different model fit for each multiply imputed dataset. This section displays models fit on the first multiple imputation of the data.

Exhibit D-1 shows the model fit for program completion. The model finds that several exogenous characteristics are associated with lower rates of program completion, including: younger participants age 20 or less (-0.26); those who expect to work at least 20 hours per week in the next few months (-0.22); those with current or prior employment in the accommodation or food service industry (-0.35); and expected program duration in months (-0.19). Characteristics associated with higher rates of program completion include sex (female, 0.43); prior college credit (0.25); not currently employed but worked in the prior year (0.19); prior employment in the healthcare or social assistance industry (0.71); and enrollment in a program targeting a goods-producing industry.

These results generally appear to be plausible and in line with expectations. For example, participants who plan to work at least 20 hours a week during training would be expected to have less time to spend on their classes and have lower completion rates than those who do not plan to work. In addition, participants with prior college credit have shown they can be successful in a college setting and thus are more likely to complete their programs.

Exhibit D-1. Model for Program Completion in Terms of Exogenous Factors

Exogenous Factor	Regression Coefficient	Standard Error	p-Value
Intercept	0.26	0.65	.690
Age 20 or less	-0.27	0.12	.020
Female	0.43	0.15	.003
Highest level of education at program entry:			
Technical, trade or vocational degree	0.35	0.22	.103
Some college credit, but no degree	0.25	0.11	.020
Employment history at program entry:			
Not currently employed but employed in last year	0.19	0.10	.066
Expecting to work at least 20 hours per week in the next few months	-0.22	0.12	.063
Currently or recently employed in accommodation or food service industry	-0.35	0.16	.031
Currently or recently employed in healthcare or social assistance industry	0.71	0.22	.001
Target industry is goods producing	0.68	0.10	<.001
Expected program duration in months	-0.19	0.01	<.001
County employment ratio for working age population	0.94	0.93	.313

Exhibit D-2 shows the model fit for training-related employment. Several characteristics are associated with lower rates of training-related employment, including race (non-Hispanic black, -0.69); annual family income less than $15,000 (-0.34); SNAP receipt (-0.54); no experience in target industry (-0.67); and a transformed measure of expected program duration in months (-0.30). Characteristics associated with higher rates of training-related employment include speaking a language other than English at home (0.43); planning to study full-time (0.47); career advancement as the most important reason for enrolling in training (0.22); prior employment in the healthcare or social assistance industry (0.85); enrollment in a program targeting a goods-producing industry (0.47); and those age 25 to 34 who were employed at program entry (0.40).

These results generally seem to be plausible – economically disadvantaged groups and those with no experience in the target industry have lower rates of training-related employment, while those who plan to study full-time, were already employed at program entry, and who rated career advancement as the most important reason for training had higher rates of training-related employment.

Exhibit D-2. Model for Training-Related Employment in Terms of Exogenous Factors

Exogenous Factor	Regression Coefficient	Standard Error	p-Value
Intercept	-2.20	0.78	.005
Black (Non-Hispanic)	-0.69	0.15	<.001
Annual family income less than $15,000	-0.34	0.13	.008
SNAP receipt at program entry	-0.54	0.19	.005
Speaks language other than English at home	0.43	0.12	<.001
Plans to study full-time	0.47	0.11	<.001
Most important enrollment reason was career advancement	0.22	0.12	.060
No experience in target industry	-0.67	0.11	<.001
Currently or recently employed in healthcare or social assistance industry	0.85	0.19	<.001
Target industry is goods producing	0.47	0.11	<.001
Expected program duration in months (squared and then divided by 100)	-0.30	0.07	<.001
Aged 25 to 34 and currently employed at program entry	0.40	0.14	.004
County employment ratio for working age population	2.11	1.08	.502

Exhibit D-3 shows the model fit for change in earnings. The regression coefficient gives the effect of the exogenous factor on the change in earnings; a positive coefficient indicates a larger change in earnings, while a negative coefficient indicates a smaller change in earnings.

Exhibit D-3. Model for Change in Earnings in Terms of Exogenous Factors

Exogenous Factor	Regression Coefficient	Standard Error	p-Value
Intercept	$3,916	$307	<.001
Not currently employed but employed in last year	-$1,422	$304	<.001
Not expecting to work for pay in coming months at program entry	-$1,357	$349	<.001
Expected program duration in months	$135	$30	<.001
Quarterly wages for 3rd quarter prior to program entry (in thousands)	-$364	$46	<.001

Notes: A positive regression coefficient indicates that the exogenous factor is associated with a larger change in earnings, while a negative coefficient indicates that the exogenous factor is associated with a smaller change in earnings.
The coefficient in the last row indicates that each additional $1,000 in earnings in the 3rd quarter before program entry is associated with a $364 smaller increase in earnings

Since this outcome measures the difference in earnings between the fifth quarter after program entry and the third quarter before program entry, the exogenous factors selected by the model may influence the outcome by their effect on either pre-enrollment or post-enrollment earnings. Two of these measures appear to affect the outcome through their influence on pre-enrollment earnings: those not currently employed but who worked in the last year had a much smaller increase in earnings ($1,422 smaller) than other groups, likely because participants in this group had high pre-enrollment earnings. More directly, those with higher quarterly wages in the third quarter before program entry had a smaller increase in earnings ($364 smaller increase for each additional $1,000 in the third quarter before program entry).

Two other factors are associated with the change in earnings. Those not expecting to work for pay in the coming months at program entry had a smaller increase in earnings ($1,357 smaller), perhaps reflecting a weak connection to the labor market. Expected program duration in months is associated with a larger increase in earnings ($135), which could be due to greater labor market returns from longer training programs.

Exhibit D-4 shows the model fit for receipt of poverty. A number of demographic and socio-economic characteristics are associated with higher rates of poverty at follow-up, including: race/ethnicity (non-Hispanic black), living with own children but no spouse or partner; low levels of education; low levels of family income; receipt of public assistance benefits; and expectations for no or limited work hours in the coming months. Characteristics associated with lower rates of poverty include: non-Hispanic white; living with spouse or partner but no children; owning a home; being employed at program entry; and family income.

Exhibit D-4. Model for Poverty in Terms of Exogenous Factors

Exogenous Factor	Regression Coefficient	Standard Error	p-Value
Intercept	-0.26	0.32	.424
Race/ethnicity:			
Black (Non-Hispanic)	0.29	0.14	.038
White (Non-Hispanic)	-0.54	0.12	<.001
Family structure:			
Lives with own children but no spouse or partner	0.40	0.15	.007
Lives with spouse or partner but no own children	-0.37	0.18	.039
Did not graduate high school and no GED	0.58	0.25	.023
Annual family income less than $15,000	0.89	0.30	.003
Annual family income between $15,000 and $29,999	0.42	0.22	.057
Homeowner	-0.32	0.16	.044
SNAP receipt at program entry	0.60	0.16	<.001
Employed at program entry	-0.38	0.12	.001
Not expecting to work for pay in coming months at program entry	0.32	0.13	.018
Expecting to work at 1-19 hours per week in the next few months	0.68	0.21	.001
Family income (in ten thousands)	-0.20	0.06	<.001
Living in poverty and program entry	0.07	0.16	.672

Exhibit D-5 shows the model fit for receipt of public assistance benefits. A number of socio-economic characteristics have a relationship with receipt of public assistance benefits. Participants with more education; who were employed at program entry, and who had higher levels of family income have lower rates of public assistance benefits receipt. Participants who had lower levels of family income; were receiving TRA, SNAP, or TANF at program entry; who did not expect to be working for pay in the coming months; and who previously served in the military had higher rates of public assistance benefit receipt.

Participants enrolled in longer programs tended to have slightly higher rates of benefits receipt—perhaps due to loss of income from being enrolled in a longer program. Living rent-free at program entry is associated with a lower rate of public assistance benefit receipt; perhaps these were younger participants living with their parents at program entry.

Exhibit D-5. Model for Receipt of Public Assistance Benefits in Terms of Exogenous Factors

Exogenous Factor	Regression Coefficient	Standard Error	p-Value
Intercept	-1.01	0.86	.240
Highest degree at program entry was AA	-0.75	0.28	.008
Annual family income less than $15,000	0.21	0.17	.198
Live rent-free at program entry	-0.43	0.15	.004
TRA receipt at program entry	1.69	0.38	<.001
SNAP receipt at program entry	2.16	0.17	<.001
TANF receipt at program entry	0.68	0.50	.177
Employed at program entry	-0.31	0.14	.026
Not expecting to work for pay in coming months at program entry	0.37	0.15	.013
Veteran	0.89	0.20	<.001
Family income (in ten thousands)	-0.10	0.03	<.001
Expected program duration in months	0.03	0.01	.001
County employment ratio for working age population	-1.03	1.22	.399

D.3. ASSUMPTIONS REQUIRED FOR CAUSAL INFERENCE

The methods described in this appendix are asymptotically equivalent to using equation C-3 for inference. As is well known, estimates of I_g for equation C-3 can be consistent estimates of the average treatment effect under the conditional independence assumption (CIA) (Angrist and Pischke, 2008). Under this assumption, the potential outcome under service receipt must be conditionally independent of service receipt given the covariates in the model, and the potential outcome under lack of service receipt must also be conditionally independent of service receipt given the covariates in the model. The team anticipated doing this kind of analysis when designing the BIF and endeavored to capture the variables that would make the CIA at least somewhat plausible. However, as discussed in the main body of the text, there are several plausible phenomena that would lead to violations of CIA in this application. The text discusses these possibilities in more detail—particularly the box **Analytic Methods and Interpreting Service Receipt Impacts** in the introduction of Chapter 6.

Some researchers may wonder why we did not use some other methodology. There are many available choices. One popular choice is propensity matching (also explained in Angrist and Pischke, 2008, among many other papers and textbooks). This method involves modeling service receipt rather than the outcome. The team decided against propensity matching because we had a larger number of services of interest than outcomes. By modeling four outcomes rather than 11 services and four service bundles, we reduced the modeling effort. Both methods are equally vulnerable to violations of the CIA.

E. Methodology for Estimating Outcomes by Program

This Appendix describes statistical methodology used to address Research Question 8:

> *How do success rates (program completion, employment in targeted field and earnings) vary across programs and grantees?*

This Appendix is organized as follows. Section E.1 sketches the methodology. Section E.2 illustrates how the complex methodology improves upon naïve estimates of local outcomes. Section E.3 goes into full detail on the methodology. This last section speaks to a more specialized audience than the earlier sections. It contains details sufficient for understanding and reproduction of our work by other statisticians. Finally, Section E.4 provides a technical discussion of the application of the methodology to TAACCCT. Most critically, this section discusses the evidence about the true level of outcome variation across TAACCCT programs.

E.1. METHODOLOGY SKETCH

One approach to estimating local outcomes would be to simply report the observed mean for each program. The team did not use this approach in Chapter 7 of this report because many of the programs had very small sample sizes. As such, the simple reported means would be very noisy and therefore poor predictors of how future cohorts of students might fare at these programs. As discussed in Chapter 5, outcomes varied considerably by baseline characteristic. Assuming that these relationships are fairly stable across programs and that the profile of students attracted to a program in the future, the team used these relationship to adjust the local means. These profile variables are shown in **Box E-1**. Moreover, the team used estimates of the measurement error on each naïve local mean to estimate the likely true long-run future variation in mean outcomes across the programs. The team used this estimated true cross-program variation to further adjust the local means so that the adjusted estimate for each program is the "best" predictor of the true long-run outcome for that program. The word "best" here has a specific meaning in statistical theory as is explained at greater length in Section E.3, but it loosely means that statisticians do not know how to prepare a better prediction for the program given the available information and a particular framework for judging quality.

As it turns out, statisticians are divided into three competing schools of how to prepare these "best" estimates based on competing understandings of what is meant by the concept of probability and how best to incorporate theories about the underlying processes as well as the design of data collection. The team used an approach from what is known as the Bayesian school of statisticians, named after a 18th century cleric and philosopher by the name of Reverend Thomas Bayes. In this school of thought, the probability that a participant will, for example, complete a particular program is not a fixed unknown number. Rather, this probability is a random quantity that has uncertainty associated with it. Different researchers can have different prior sets of beliefs about this probability before the data are observed. These prior beliefs are expressed in the form of a prior distribution. After data are observed, these beliefs are updated following certain mathematical rules spelled out by Bayes theorem. These updated beliefs are expressed in the form of a posterior distribution. The mean, variance and percentiles of this posterior distribution are commonly reported.

None of the other analyses in this report use a Bayesian approach. Instead, the team used frequentist approaches for the other chapters. Chapters 4 and 5 use the "design-based" frequentist approach and Chapter 6 uses a "model-based" frequentist approach. These are the other two competing schools of statistical thought. In both frequentist schools, the probability of a particular participant completing a particular program is a fixed but unknown constant. In the design-based frequentist approach, the analyst makes no assumptions about underlying processes other than that there are no wild true outliers in the population like program participant getting a 7-figure annual salary as a result of completing one of the studied programs. In the model-based frequentist approach, the analyst makes assumptions about the process leading to the fixed but unknown parameters of interest. Examples of these assumptions include things like assuming that change in earnings is normally distributed (i.e., follows a bell-shaped curve) or assuming that the effect of a service on the likelihood of program completion does not vary by program.

Box E-1.
Student Profile Variables

- Age: (4 levels)
- Female
- Race/Ethnicity: (4 levels)
- Family structure: (4 types)
- Educational Attainment: (6 levels)
- Family Income: (3 levels)
- Home tenure: (3 levels)
- Public assistance: (four programs)
- Employment status & duration of unemployment: (4 levels)
- Expect Work Hours while in training: (4 levels)
- Citizenship & Veteran status: (3 levels)
- Language Other than English spoken at home
- Plans to study Full Time
- Primary Reason to Enroll: (5 reasons)
- Work Experience: (3 levels)
- Poverty status at Baseline: in poverty
- Training Targets the Goods-producing Industry Super Sector
- Program Length, Months
- Current or Previous Employment in Manufacturing

Additional Student Profile Variables available for outcomes other than earnings

- Logarithm of family income
- Local employment rate (county-level employment as percent of total population 18-64)

In most of their professional work, the team prefers the design-based frequentist set of rules and customs for analysis. However, the work in Chapters 6 is focused on understanding underlying processes, so it made sense to use model-based frequentist rules and customs for it. All three schools of statistical thought can produce estimates of mean outcomes by program. The team found the use of the design-based frequentist approach to be inadequate for this task because this method only uses local information. As a result, if the sample size is small (as it is for many programs studied in this report), the estimate will have such a high variance as to be practically useless. Model-based frequentist methods can fix this issue, but the team rejected them for the analyses in

Chapter 7 because of the methodological problems in the available variance estimates on local outcomes. These methods are forced to neglect that the uncertainty caused in adjusted local means by having to estimate the true between-program variance. Only Bayesian methods can both reduce the variances enough to make the local estimates useful and also provide fair variances on those adjusted local estimates.

Section E.2 illustrates the properties of the Bayesian estimates of local outcomes in contrast to those of the design-based frequentist approach, labeled as "direct" estimates. The direct estimates fully captures the idiosyncratic features of each program but will generally have large variances, as the sample sizes of programs are not particularly large. The Bayesian methods combine idiosyncratic results with what we should expect based on the profile of program participants and statistical models for how the characteristics of participants at program entry influenced their outcomes. These models were generalizations of simple regression models. In addition to student profiles, the models also used program duration and the local employment rate in the working age population.[7]

Generally speaking, we expect that Bayesian estimates will improve upon the direct estimates in two ways. First, the Bayesian estimates will be better aligned with expected results based on the participant profile, program duration, and the local employment rate. Second, the width of the error bands will be much shorter. When the statistical model has little to no explanatory power (i.e., outcomes cannot be predicted by demographics and baseline variables), Bayesian estimates will be very similar to the design-based estimates, with some shrinkage towards the overall mean. When the model is highly predictive, Bayesian intervals will be shorter, especially for programs that have low sample sizes, but have the participant profile similar to that in some other programs in the study.

It is important to note that the Bayesian estimates can also be worse than direct estimates. This can happen two different ways. First, it could happen that one program does a much better or worse job of serving a particular participant group (such as men with education below high school) than is the case at all or most of the other programs. If this happens, the adjustment is based on a faulty assumption and as a result, the adjusted estimate may be further from the truth than the direct estimate. Second, it can happen that the true distribution of participant means across programs is different than the assumed distribution. For example, instead of the means being normally distributed across programs with constant variance, it might happen that there are two groups of programs, one that turns out certified nursing assistants who make $11 per hour and one that turns out bachelors of chemical engineering that made $60 per hour. If this bifurcation was not part of the prediction model, then the mean participant-level residual at the program level would not follow a bell-shaped distribution. Instead, there would be two bells, sort of like a Bactrian camel. Assuming one hump when there are really two would result in the Bayesian procedure shrinking the program estimates for both groups of programs into the valley between the two humps, probably resulting in all of them being worse than the direct estimates. While the team checked the distribution of program-level mean person-level residuals for signs of non-normality, departures from normality are difficult to detect with just 34 programs.

[7] Technical constraints preventing merging geographic information on local employment rates to the earnings data in the NDNH, but this variable was used for the other outcomes.

E.2. RESULTS

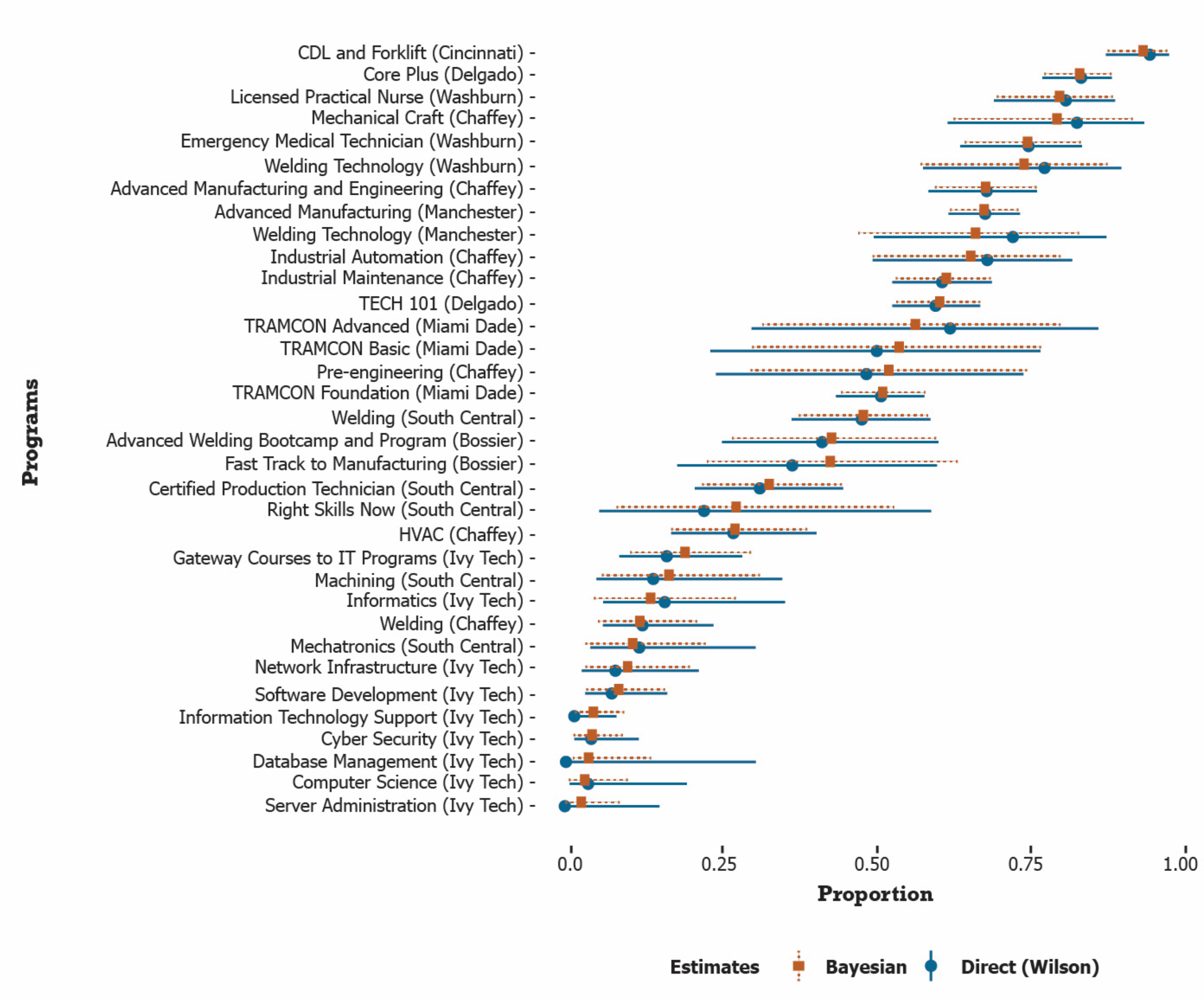
We present the key results graphically in the form of comparison of direct and Bayesian estimates. We use the same style plots as used in Chapter 7, but overlay the two competing estimates. These plots are known as caterpillar plots for obvious reasons. They involve sorting the programs from worst to best—based on the Bayesian estimates of the local program mean. Note that caterpillar plots in Chapter 7 showed 80 and 99.9 percent credible intervals. The plots below directly display the 95% confidence intervals computed from the design-based estimates and standard errors, which only use information contained solely within a given program; and model-assisted 95% Bayesian credible intervals that incorporate a model for the outcome. To the extent that the model is predictive of the outcome, we hope to see that the latter intervals are shorter. The design-based frequentist interval reported is the Wilson interval (Dean and Pagano 2015). This section shows these overlaid caterpillar plots for the same four outcomes studied in Chapter 7. In each of these, the orange squares mark the Bayesian estimates, the orange lines mark the Bayesian 95 percent credible intervals, the blue dots mark the direct estimates, and the blue lines mark the direct 95 percent confidence intervals.

E.2.1 PROGRAM COMPLETION

Exhibit E-1 shows the two sets of estimates of program completion rates by program. For this outcome, the two sets of estimates are fairly similar. Few programs would be ranked differently using the direct estimates and the credible intervals are not much shorter than the confidence intervals. For example, the short-term CDL and Forklift programs at Cincinnati State have the highest completion rates under either estimation strategy, and the two-year Server Administration program has the lowest. The reason that two sets of estimates are similar for this outcome is that between-program variance was estimated to be very large, indicating that it was dangerous to use cross-program information to adjust the estimates very much.

Exceptions to this general rule exist. For example, the Bayesian procedure estimates a lower completion rate for the Welding Technology program at Manchester Community College than estimated by the design-based frequentist procedure. In the other direction, the Bayesian procedure estimates a higher completion rate for Right Skills Now program at South Central College than estimated by the design-based frequentist procedure. Another exception concerns the width of the intervals for Database Management program at Ivy Tech. The design-based frequentist procedure is blind to completion rates at other programs and thinks that the completion rate at this program could be anywhere between 0 and 30 percent. In contrast, the Bayesian procedure looks at completion rates at other programs and concludes that the completion rate is unlikely to be larger than 15 percent.

Exhibit E-1. Program Completion Rate, by Program – Overlaid Bayesian and Direct Estimates

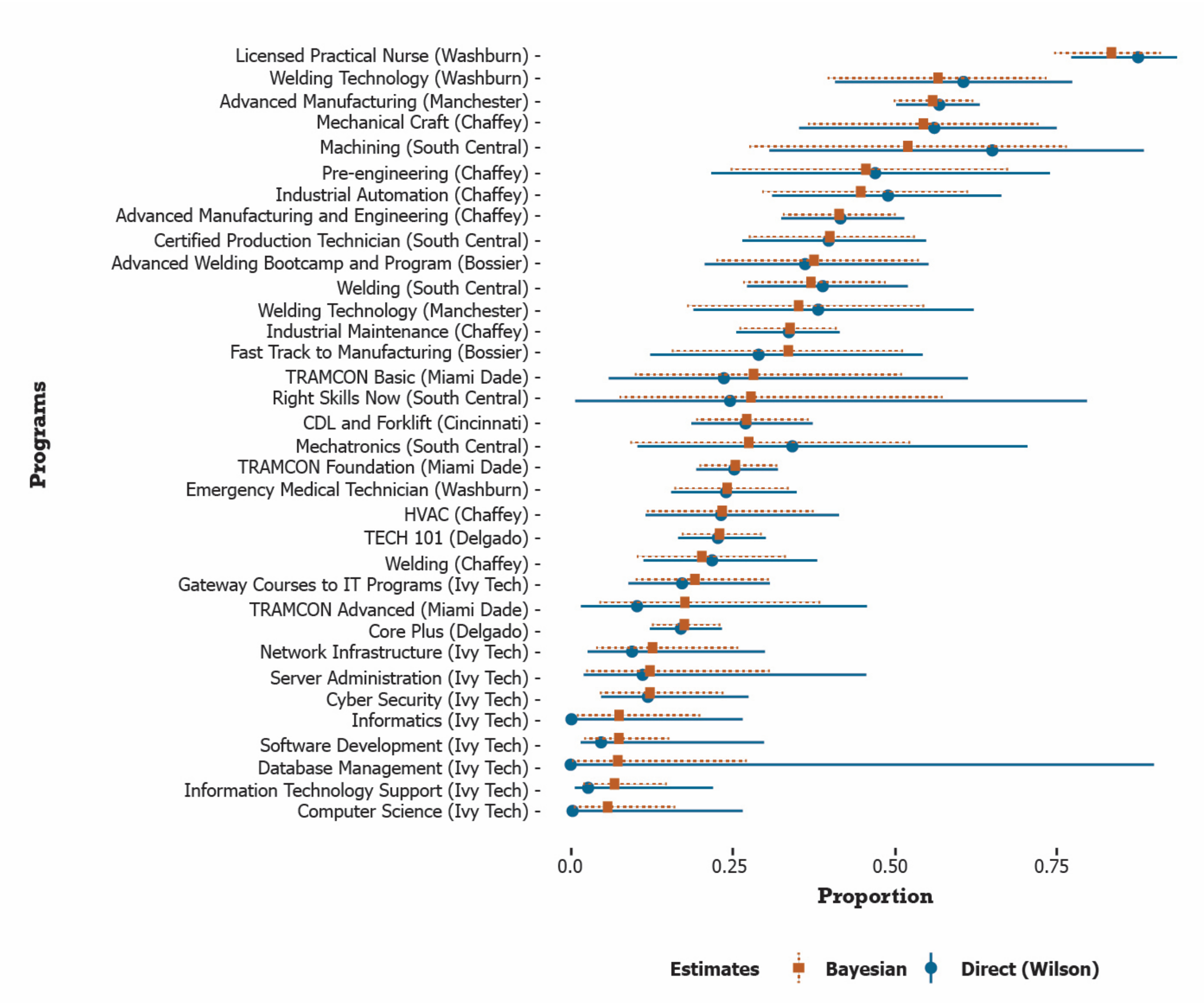


E.2.2 TRAINING-RELATED EMPLOYMENT

The Bayesian procedure made slightly stronger adjustments to the direct estimates for this outcome than for program completion, but the estimated between-program variation was large for this outcome as well as for program completion, so the adjustments are still mild. Both methods agree on which program is best at helping their participants obtain employment related to their training (the Licensed Practical Nurse program at Washburn University) and which is worst (the Computer Science program at Ivy Tech).

As for program completion, several exceptions exist. For example, the Bayesian procedure was much more pessimistic than the direct estimates about the chances of future cohorts of participants in the Machining program at South Central College. In the other direction, the Bayesian procedure was more optimistic than the direct estimates about the chances of future cohorts of participants in five of the programs at Ivy Tech (Informatics, Software Development, Database Management, Information Technology Support, and Computer Science). Also, the Bayesian procedure provided much tighter error bars for six of the programs.

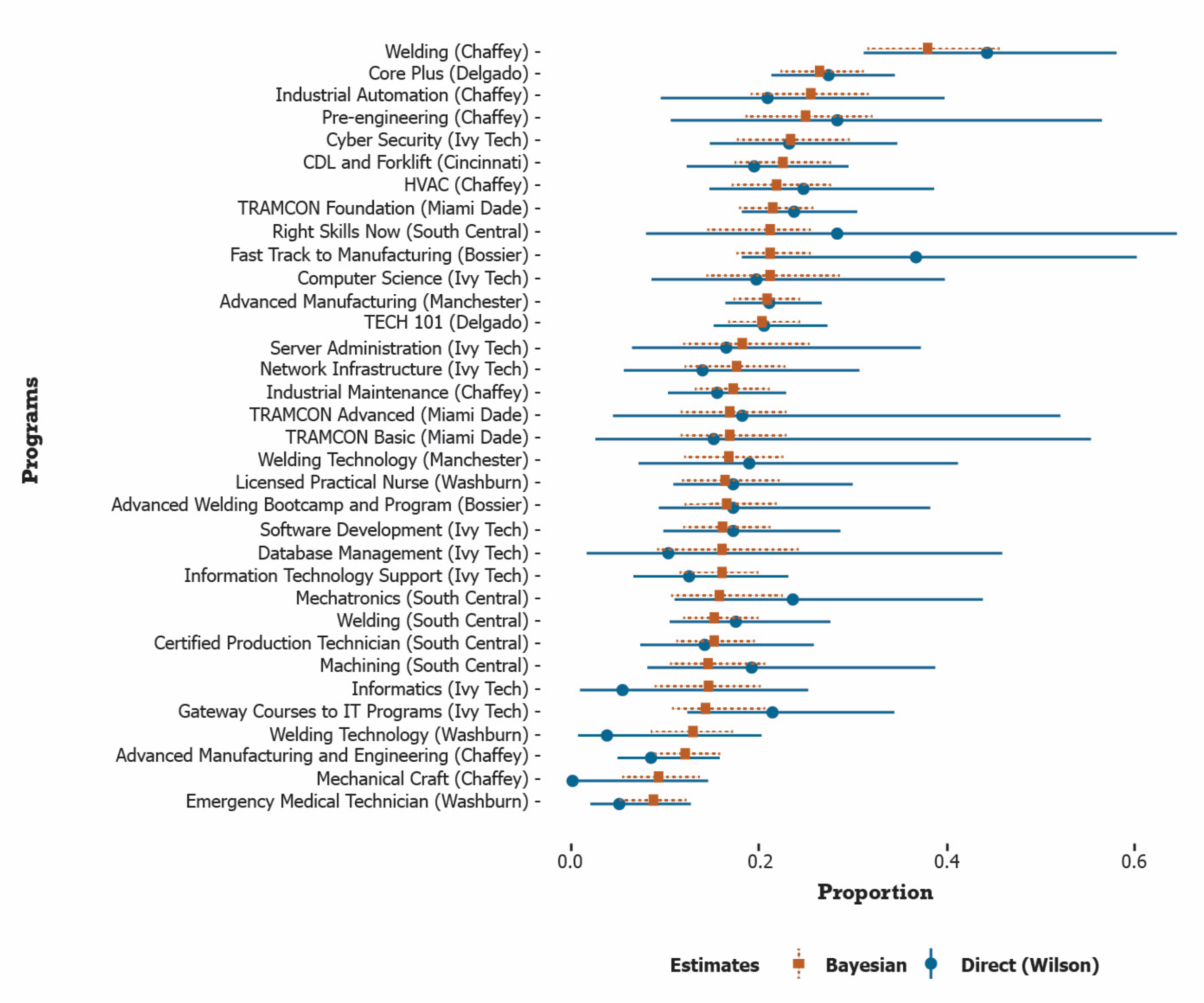
Exhibit E-2. Training-related Employment Rate, by Program – Overlaid Bayesian and Direct Estimates (Subset to participants not still enrolled at survey follow-up)



E.2.3 PUBLIC ASSISTANCE BENEFIT RECEIPT

For this outcome, the differences between the Bayesian and direct estimates are much sharper than for program completion or training-related employment. For this variable, caterpillar plots demonstrate that Bayesian credible intervals are much shorter that the frequentist intervals. Also note that the "spine" of the caterpillar is much closer to vertical than would be the case if the programs were sorted by the design-based frequentist estimates. Both features are due to the fact that the estimate of between-program variance on this outcome was very small.

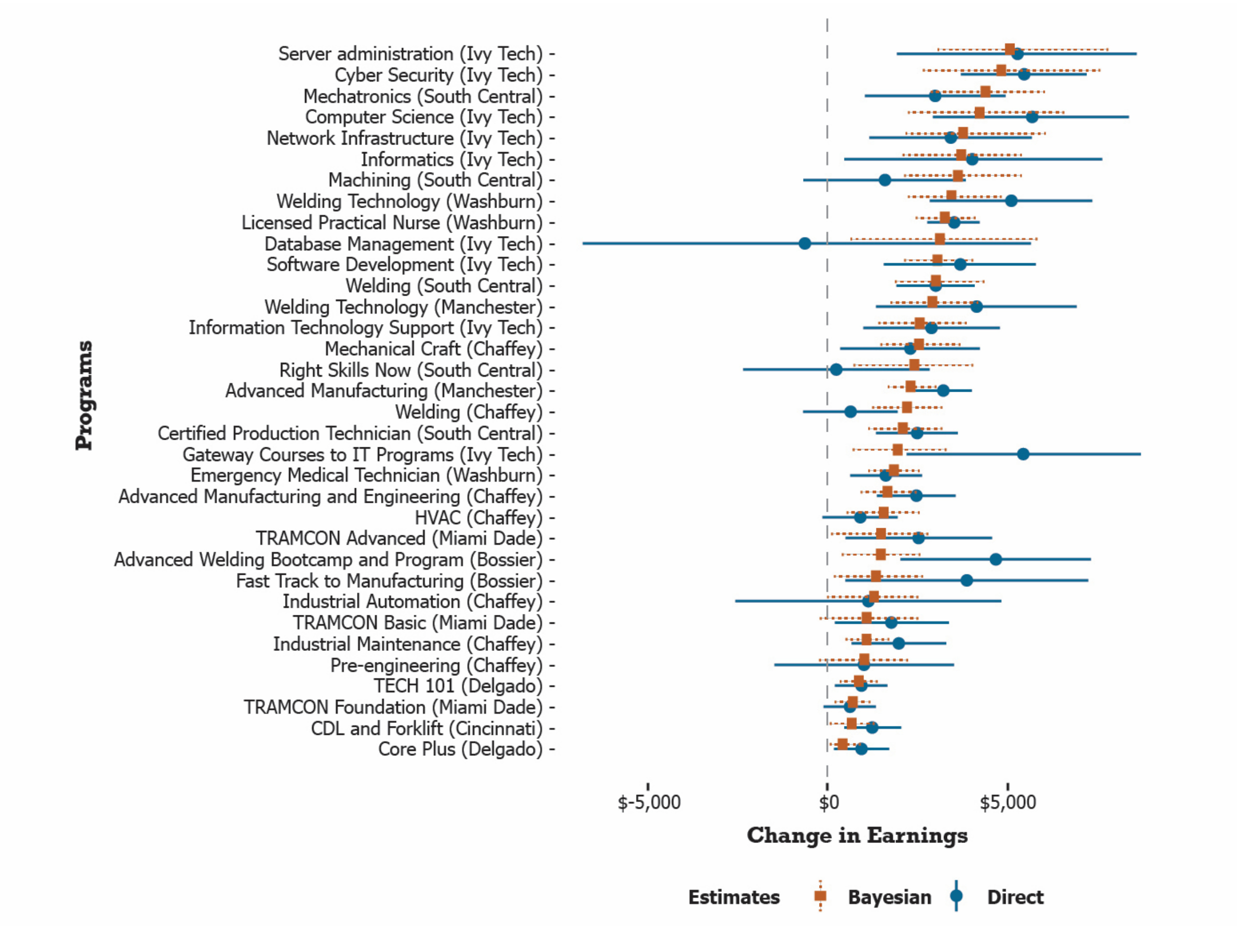
Exhibit E-3. Public Assistance Benefit Receipt, by Program – Overlaid Bayesian and Direct Estimates



E.2.4 CHANGE IN EARNINGS

The last outcome analyzed is the growth of earnings in two years from three quarters before the program start to five quarters after. While the above three outcomes are binary, and are based on self-reports in the follow-up survey, the difference in earnings is a continuous variable, and is based on the NDNH administrative data. For this outcome, the differences between the Bayesian and direct estimates are also quite sharp. The caterpillar plots demonstrate that Bayesian credible intervals are much shorter than the frequentist intervals.

Exhibit E-4. Change in Earnings, by Program – Overlaid Bayesian and Direct Estimates (Subset to participants not still enrolled at survey follow-up)



E.2.5 SUMMARY

Comparing the results qualitatively among the four variables, we can confidently speak about the potential strength of Bayesian estimation procedures. While precision gains were modest for the program completion and training-related employment, due to high variability of the outcome rates between programs, and low predictive power of the models, the estimates generally almost coincided. For public assistance benefit receipt and change in earnings, the Bayesian model demonstrated very strong predictive power that resulted in substantial precision gains.

E.3. METHODOLOGY DETAILS

This final section is highly technical. These details are provided to aid future researchers who may either try to reproduce the current results or apply the methodology to similar research projects.

E.3.1 GENERALIZED LINEAR MIXED MODELS

For program completion, training-related employment, receipt of public assistance (all based on the Follow Up survey data), and growth in earnings (NDNH data), we posit generalized linear mixed models that include random effects that account, at least partially, for the idiosyncratic workings of each program:

Outcome: $y_{ji} \sim f\left(y_{ji} \middle| \theta_{ji}, \sigma\right)$
Linear index: $\theta_{ji} = \alpha + X_{1ji}\beta_1 + \cdots + X_{pji}\beta_p + u_j,$
Mean (inverse link): $\mu_{ji} = E\left[y_{ji} \middle| \theta_{ji}\right] = g^{-1}\left(\theta_{ji}\right),$
Program random effect: $u_j \sim N(0, \tau^2)$

where j indexes programs, i indexes students within programs, u_j is a normally distributed idiosyncratic program random effect, and $f(\cdot)$ is an appropriate distribution. For a continuous response (e.g. change in earnings), $f(\cdot)$ is usually chosen to be normal (i.e. $y_{ji}|\theta_{ji}, \sigma \sim N(\theta_{ji}, \sigma^2)$) although for the growth in earnings (a difference of two highly skewed distributions), a heavier tailed alternative is called for, e.g. $y_{ji}|\theta_{ji}, \sigma \sim Cauchy(\theta_{ji}, \sigma)$ with density

$$f(y|\theta, \sigma) = \frac{1}{\pi\sigma\left[1 + \frac{(y-\theta)^2}{\sigma^2}\right]}$$

For binary 0/1 outcomes (the primary outcomes based on self-report in the follow-up survey: receipt of public assistance benefits, employment in a job related to training, and program completion), the appropriate distribution is binomial, most often used with the canonical logit link:

$$\text{Prob}\left[y_{ji} = 1 \middle| \theta_{ji}\right] = \mu_{ji} = \frac{\exp\left(\theta_{ji}\right)}{1 + \exp\left(\theta_{ji}\right)}$$

(The scale parameter σ is not relevant for the binomial distribution.)

One of the most important parameters of the above model is the variance of the random effects, τ^2. It controls the degree of homogeneity of the programs and the extent to which the program-idiosyncratic effects impact the program performance. While the goal of the exercise of building a statistical model like the above is to improve program-level predictions, larger values of this parameter make this task more difficult. In some cases, e.g. in linear models, it can be explicitly shown that, holding everything else constant, the larger values of τ^2 lead to a lesser weight that the statistical model has in the resulting estimates, and correspondingly a greater weight is being placed on the direct estimates (weighted means of outcomes within the program).

For a set of estimates of the model parameters $\hat{\alpha}, \hat{\boldsymbol{\beta}}, \hat{\tau}, \hat{\phi}$, the model-assisted *composite* estimate of the average outcome θ_j for the *j*-th program is:

$$\hat{\theta}_j = \frac{1}{n_j}\sum_{i \in j} \hat{\mu}_{ji} = \begin{cases} \frac{1}{n_j}\sum_{i \in j} \int \frac{\exp\left(\hat{\theta}_{ji}\right)}{1 + \exp\left(\hat{\theta}_{ji}\right)} f(\hat{u}_j | \{X_{ji}, y_{ji}\})\, d\hat{u}_j, \text{binary outcome,} \\ \frac{1}{n_j}\sum_{i \in j} \hat{\theta}_{ji}\, \text{, continuous outcome} \end{cases}$$

$$\hat{\theta}_{ji} = \hat{\alpha} + X_{1ji}\hat{\beta}_1 + \cdots + X_{pji}\hat{\beta}_p + \hat{u}_j$$

The integral for the binary outcome is with respect to the posterior distribution of the random effects (either empirical Bayes distribution, obtained by plugging the MLE estimates; or the full Bayes when full Bayesian estimation is undertaken through MCMC), while for the continuous outcome, the posterior mean is used. Although this composite estimate is biased, it generally has smaller mean square error (MSE) than the direct estimate $y_j = \frac{1}{n_j}\sum_i y_{ji}$ because reduction in variance outpaces increase in (squared) bias.

Since bias and variance both contribute to the projections of future performance, estimators that minimize MSE are generally preferred for forward projections.[8] If τ^2 is large, the MSE reduction will be trivial and the composite estimates will be similar to the direct estimates, but otherwise, the MSE reduction can be substantial, particularly for programs with small local sample sizes. Note that τ^2 is a residual variance at the program level, so if the covariates are powerful predictors of the outcome, then this variance will be small, and, as a result, the MSE should be reduced for nearly all local programs. However, even with small τ^2, if the local sample size is large, then the difference between the composite estimate and the direct estimate will be small. In this case, the variances will also be very similar.

Intuitively, the variance reduction when both the local sample size and τ^2 are small arises from the fact that the "fixed" part of the model $(\hat{\alpha}, \hat{\boldsymbol{\beta}})$ is estimated on the entire sample rather than just on the local sample. This is often referred to as "borrowing strength" across programs. In this case, since student outcomes are largely determined by their characteristics at baseline, the mean outcome for any one local program is quite accurately estimated by using the outcomes for similar students across all the programs. This borrowing of strength tends to "shrink" program-specific estimates toward the average prediction of the outcome propensity based on the covariates observed for the participants of the program. (In a simple case of no predictors, the shrinkage is toward the overall mean across all programs.)

On the other hand, if τ^2 is large, it is an indication that the variation in student outcomes across programs is not explained by the covariates, and that local program features are much more determinative than students' incoming profiles. In this case, borrowing of strength is not helpful and so there is minimal shrinkage of local program estimates toward the average fixed-effects-only prediction.

To further aid intuition about the nature of these model-assisted estimates, note that they can be approximately represented as

$$\hat{\theta}_j = \phi_j \sum_{i \in j} \hat{\mu}_{ji} / n_j \; + (1 - \phi_j) \sum_{i \in j} y_{ji} / n_j$$

The term $\sum_{i \in j} \hat{\mu}_{ji} / n_j$ is the *model-based* estimate of the outcome / completion rate at program *j*. While reflecting the demographic makeup of the program participants, it does not capture any other idiosyncratic features of a program, where idiosyncratic features are those that cannot be explained by known factors – in this case the student profile at program entry, the program duration, and the local employment rate among the working-age population. By definition, if a program has a particularly good workshop for skills practice, a particularly engaging curriculum, or a particularly good instructor, none of the positive outcomes due to these factors will be captured in this component. In contrast, the term $\sum_{i \in j} y_{ji} / n_j$ is the *direct estimate* of the completion rate at the same program. It fully captures the

8 Rao and Molina (2015, Chapter 5).

idiosyncratic features but will generally have much larger variance than the first term, as the sample sizes of programs are not particularly large. The *compositing factor*

$$\phi_j = \frac{\mathrm{var}(\sum_{i\in j} y_{ji}/n_j)}{\mathrm{var}(\theta_1,\ldots,\theta_{34}) + \mathrm{var}(\sum_{i\in j} y_{ji}/n_j)} = \begin{cases} \dfrac{\theta_j(1-\theta_j)/n_j}{\mathrm{var}(\theta_1,\ldots,\theta_{34}) + \theta_j(1-\theta_j)/n_j}, \text{binary outcome} \\ \dfrac{\sigma^2/n_j}{\mathrm{var}(\theta_1,\ldots,\theta_{34}) + \sigma^2/n_j}, \text{continuous outcome} \end{cases}$$

represents the extent to which information from other programs can be utilized to inform estimation for program j. Here, $\hat{\theta}_j$ is the true long-run program outcome rate (e.g., completion, or use of public assistance) for students at program j if the program continues to be operated under the same general conditions. When large sample sizes are available for that program, and/or there is substantial idiosyncratic variation across programs, the numerator term is small compared to the population between-program variance $\mathrm{var}(\theta_1,\ldots,\theta_{34})$ of program-specific outcome rates, and hence the fraction ϕ_j of the model-based estimate in the composite estimate is small, so the composite estimate will be approximated equal to the direct estimate for the program. On the other hand, if there is very little idiosyncratic variation across programs and if the local sample size is small, $n_j \to 0$, the numerator term dominates the between-program variance, and $\phi_j \to 1$ indicating that the analyst has to rely on the model more and more to produce meaningful estimates.

It is worth noting that throughout the process, the analyst does not interpret the model coefficients $\alpha, \boldsymbol{\beta}, \tau, \phi$, does not conduct inference for these, and does not attempt to address their marginal effects on the outcome. In other words, the regression model plays only a predictive role. It thus relieves the analyst from concerns that are often relevant to structural econometric models, such as endogeneity of explanatory variables, omitted variable biases, and correlations between regressors and random effects. Whatever helps improving the predictive performance of the model works for SAE.

Model-assisted small area estimators of this type that blend local (e.g., state, county, school, program, class, grantee) experiences with experiences of similar persons in other areas (states, counties, schools, programs, classes, grantees) have well established methodologies (Rao and Molina 2015) and are common in many federal statistical agencies. Perhaps best known are the school-district level estimates of child poverty[9] produced by the Census Bureau for the purpose of allocating Title 1 education funds and the local estimates of cancer risk factor and screening behaviors[10] produced by the National Cancer Institute. Procedures like these are also used in evaluations of school and hospital quality, athlete quality (in professional sports), and stud quality (in animal science), among other fields.[11] Estimators of this sort are sometimes referred to as "best" estimators because minimize the mean squared error in the estimate about the likely success of future participants rather than narrowly focusing on the experiences of the set of participants who happened to attend during the study period and who might have brought unmeasured skills and handicaps (i.e., omitted variables) with them.

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9 https://www.census.gov/programs-surveys/saipe.html [last accessed December 20, 2019]

10 http://sae.cancer.gov/ [last accessed December 20, 2019]

11 For an introduction to the many uses of such models, see for example Hox (2010).

E.3.2 BAYESIAN ESTIMATION

Estimating the variance of $\hat{\theta}_j$ accurately is extremely difficult with frequentist methods. A common approach is to treat the estimated between program variance τ^2 as known rather than estimated. This dramatically simplifies variance estimation, but also leads to systemic underestimation of the variance of $\hat{\theta}_j$ unless the number of programs is very large. Bayesian methods do not suffer from this same defect. With them, it is quite easy to estimate the variance of $\hat{\theta}_j$, fully reflecting the extra variance caused by uncertainty in the estimate of τ^2. However, in order to gain this simplification in the variance estimation, it is necessary to adopt the entire Bayesian framework in which probabilities are a quantification about personal beliefs or a representation of the state of knowledge about the parameters. Users of Bayesian methods often try to minimize the influence of personal beliefs by placing extremely vague priors on the parameters, going so far as to place improper priors on some of them that say that any real number is equally likely. However, it has been demonstrated that improper priors are not an option for τ^2. A proper prior on this parameter is required in order for the posterior distributions of $\hat{\theta}_j$ to be proper.

For the intercept and the regression slopes, improper priors $\alpha \sim 1, \beta_k \sim 1$ are usually chosen (leading to inference on these parameters that is similar to the frequentist inference). For the variance parameters τ, σ, distributions with support on $[0, +\infty)$ are usually chosen; popular choices are Gamma distribution with very small shape parameters and large scale parameter, log-normal, half-normal, half-Cauchy, and uniform over a sufficiently long interval that would cover plausible ranges.

The most critical prior pertaining to Research Question 8, variability of outcomes between programs, is the random effect variance parameter τ^2. The team chose priors that ran from zero to very large values in order to try to minimize the impact of the prior on the final estimates of local program effects. Keeping the range with positive support wide should allow the estimate of τ^2 to be dominated by the data rather than the preconceptions of the team.

- For the binary outcomes with logit link, the scale of the linear index θ_{ij} is commensurate with the standard deviation of logistic distribution $\frac{\pi}{\sqrt{3}} = 1.81$: a change of the linear index from 0 to ± 1.81 corresponds to a change in probability of the two outcomes from 50%/50% to 14%/86%, which is a very drastic change. Thus for the prior distribution of the random effect variance, we used the prior that was half-Cauchy(0,1) (i.e., Cauchy distribution restricted to the non-negative numbers):

$$f(\tau) = \frac{2}{\pi[1 + \tau^2]}, \tau > 0; 0 \text{ otherwise}$$

- For the continuous outcome of change in earnings, given that the quarterly earnings of program participants are of the order of tens of thousands of dollars, and one of the primary outcomes, public assistance, can be characterized by the federal poverty line of $12,490 for 1-person household, we used half-Cauchy(0,$10,000) prior distribution with the scale of $10,000:

$$f(\tau) = \frac{2}{\pi s \left[1 + \frac{\tau^2}{s^2}\right]}, \tau > 0;\ 0 \text{ otherwise}; s = 10{,}000$$

The scales of the prior Cauchy distributions are chosen to allow values of τ to cover, or to correspond to, the expected range of the θ values (the 99th percentile of the standard Cauchy distribution is 31.82).

Later diagnostics show that this distribution is sufficiently noninformative, in that the density of the posterior at the posterior mean / mode is much higher than the prior density.

Bayesian estimates are obtained in the form of posterior distributions. At conceptual level, posterior distributions represent application of Bayes theorem:

$$\text{Posterior}(\text{parameters}|\text{data}) = \frac{\text{Likelihood}(\text{data}|\text{parameters}) \times \text{Prior}(\text{parameters})}{\text{Marginal distribution of data}}$$

This formulation produces a continuous distribution that, however, is difficult to impossible to express analytically for practical purposes such as computation of the posterior means or credible intervals. Thus in practice, to conduct Bayesian inference, the posterior distribution is simulated through sampling. Markov chain Monte Carlo (MCMC) methods. These methods generate series of parameter values $(\hat{\alpha}, \widehat{\boldsymbol{\beta}}, \hat{\tau}, \hat{\sigma})$ that approximate draws from the joint posterior distribution for the vector of parameters. For details, see Gelman et al (2013) and Gill (2014). The fastest implementation of Bayesian methods currently available is Stan (http://mc-stan.org; Carpenter et al 2017). It is built upon Hamiltonian Monte Carlo (Neal 2011; Monnahan et al 2017), a set of computational techniques that draw upon the dual representation of physical systems in terms of "positions" and "moments" that evolve according to the laws of Hamiltonian dynamics.

Explanatory variables X_{kji} used in all the models are listed in **Box E-1**. To mimic model selection by lasso, independent double-exponential, or Laplace, prior distributions were used for the slope parameters β_k (Kyung et al 2010):

$$f(\beta) = \frac{1}{2s} \exp\left(-\frac{|\beta|}{s}\right)$$

where the mean is zero, and the standard deviation is $\sqrt{2}s$. For the binary outcomes, the scale s of the Laplace prior distributions for regression slopes was set to 0.25. This reflects the prior expectation that the variables, if significant, would have odd ratios of about 0.25. This corresponds to the differences in actual probabilities of 44% to 56% for the average outcome rate of 50%. For the continuous outcome of change in earnings, the scale s of the Laplace prior distributions for regression slopes was set to 2000. This corresponds to the prior expectation that the significant variables will likely affect the earning changes by $\pm$ \$2,000. The heavy tails of the Laplace distribution, however, allow for much stronger effects, while the sharp peak at zero acts to strongly prefer a modal estimate of zero lacking stronger evidence of impact of the variable on the outcome.

E.3.3 BAYESIAN DIAGNOSTICS

To ensure validity of Bayesian inference based on the simulated MCMC chains, the analyst needs to verify that the chains have converged. As it turns out, this is a difficult task. While there are no definitive checks, one should expect that the draws should form stationary processes, ideally with minimal to no autocorrelation. If there are multiple chains being run, then additionally one would expect that all of them converge on the same approximate posterior distributions. As discussed more fully below, we followed these practices. We provide the within chain and between chain diagnostics.

By default, Stan/RStan reports several measures to diagnose convergence and efficiency of the resulting chains. These include:

- Potential scale reduction factor (Gelman and Rubin 1992) $\hat{R}$, defined for multiple chains as the square root ratio of the total variance of MCMC draws to the average within-chain variance. If this statistic is 1, all chains have converged onto the same set of values. (This is hard to achieve in the current project, as each of the multiply imputed data sets implied its own set of posterior distributions that differed slightly between imputations.) It is recommended that this statistic is below 1.10 or 1.05. When only one chain is available, $\hat{R}$ is computed by splitting the chain in halves, and treating the two halves as separate chains.
- Effective sample size measures the precision of the posterior mean given the observed autocorrelations $\rho_1, \rho_2, \ldots$ between consecutive draws $\theta^{(1)}, \theta^{(2)}, \ldots, \theta^{(N)}$ of a parameter θ, relative to the ideal uncorrelated sequence. N_{eff} close to the actual number of draws N indicates effective simulation, while $N_{eff} \ll N$ indicates high autocorrelation which may in turn indicate problems in achieving convergence.

$$N_{eff} = \frac{N}{1 + 2\sum_{l=1}^{N} \rho_l}, \rho_l = \frac{s_l^2}{s_0^2}, s_l^2 = \sum_{t=l+1}^{N} (\theta^{(t)} - \bar{\theta})(\theta^{(t-l)} - \bar{\theta})$$

The actual formulae used by RStan for both $\hat{R}$ and N_{eff} differ slightly by including various small sample adjustments that improve performance of these measures with few and shorter chains.

Hamiltonian Monte Carlo has its own additional sets of tuning parameters and computational techniques to improve accuracy and convergence. In this project, Hamiltonian MCMC was run with the following tuning parameters:

- adapt_delta = 0.96, elevated from the default value of 0.8. This is the primary parameter that should be adjusted in Hamiltonian MCMC. Higher values (those closer to 1) of this parameter force the algorithm to make smaller steps thus improving the quality of numeric approximations of the Hamiltonian trajectories. While simple regression models converge fine with the default setting of 0.8, the current model is more complicated in two aspects. First, it uses random effects that effectively introduce correlations between individual observations in the data set. Second, it uses non-differentiable Laplace priors that generally require very small steps and high values of the delta parameter.[12]
- stepsize_jitter = 0.2. Jitter of step sizes is not necessary, but it helps avoid (very infrequently encountered) cyclical behaviors of chains.
- max_treedepth = 12, elevated from the default value of 10. The No-U-Turn Sampler (NUTS) implemented in Stan utilizes a physical principle of Hamiltonian dynamics that a system is bound to return to its state after a certain period of time, and evaluates the number of steps until the U-turn by attempting 1, 2, 4, 8, etc. steps, doubling the number of steps until the U-turn is encountered. This parameter caps the number of such duplications, thus limiting the number of steps along each

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[12] In his tutorial on Bayes sparse regression, one of Stan developers used an even higher value of 0.99, although in his example, the number of predictors, 200, exceeded the number of observations, 100. See https://betanalpha.github.io/assets/case_studies/bayes_sparse_regression.html#34_laplace_prior.

trajectory by $2^{\text{max\_treedepth}} - 1$. It should be set in such a way that in estimation runs, the tree depth is never saturated.

- Warmup period = 1000 iterations, estimation period = 1000 iterations. The warmup period is used to calibrate the parameters of Hamiltonian Monte Carlo, in particular the step sizes. (Small step sizes produce better approximations at the expense of slower computing; larger step sizes run the risk of approximations being so poor that the "energy" of the underlying physical system blows up to infinity, which must be avoided, e.g. by choosing a different random direction for a trajectory from the current MCMC draw.) The estimation period is used to produce the posterior draws. It is crucial that the chains shall have converged by the beginning of the estimation period.

An appropriate combination of parameters is obtained by trial and error. While demonstrating that the chains have converged is mathematically impossible, diagnostics of failure of convergence are more readily available. Beyond the diagnostics developed for other types of MCMC, such as examination of autocorrelations, traceplots, Gelman-Rubin convergence diagnostics, etc., Hamiltonian MCMC implemented in RStan provides additional diagnostics such as frequency of divergent transitions and changes in the chain "energy." A successful transition from the warmup to the estimation period in Hamiltonian MCMC can also be tracked by (1) lack of divergent steps, (2) stabilization of step size, (3) tree depth comfortably below the max depth. All of these behaviors were checked and observed in this project.

One MCMC chain was run per each of the M=12 imputed data sets. For each chain, and for the collection of chains, the Bayesian MCMC diagnostics were checked. Diagnostics specific to Hamiltonian MCMC included making sure that, in the estimation part of the chain, there are no divergent transitions (a transition is declared divergent if there is evidence that approximation of a trajectory becomes inaccurate), that mean acceptance statistic is about the same as the adaptive delta parameter, and that the treedepth never achieves its maximum. All of the chains passed these checks.

For each given imputed data set, the chain corresponding to that data set demonstrated convergence and expected performance, as gauged by the variance reduction factors R-hat being less than 1.05.

A rare exception is the random effects standard deviation τ parameter in estimation of the public assistance outcome: three out of twelve chains had R-hat values in excess of 1.1, namely 1.48, 1.17 and 1.13. This parameter also exhibited very high autocorrelations, with at least ten lags having autocorrelations greater than 0.1. Traceplots of τ indicated the reason: sometimes the chain would get stuck with values of τ very near zero that are difficult to escape. This did not appear to be only a warmup length issue, as chains would stray into values near zero from apparently stable periods where their performance would be just as good as of other chains that never visited zero. This issue however may not be particularly problematic for this outcome: since the regression model included the primary determinants of eligibility for public assistance, income and household composition, the fixed portion of the model had very high explanatory power. It is not then surprising that the remaining variation between programs was poorly identified.

When the chains were combined in order to conduct joint inference that would account for the multiple imputation, the overall posterior summaries indicated that R-hat statistics would deteriorate very substantially, with about a quarter of the variables having R-hats reported as above 1.05. This strong interaction with multiple imputation is not surprising, and reflects the between-imputation variability that is intrinsic, and is in fact desirable, for this missing data method. Put differently, each chain is estimating its own parameter corresponding to that specific imputation, and different chains center on slightly different parameter values.

Upon establishing adequate quality of Bayesian posterior draws, we computed the program-specific outcome rates $\hat{\theta}_j$ for each draw. The summaries (means and distribution percentiles) of these composite estimates are reported in Appendix G and visualized using caterpillar plots in Chapter 7. Despite variations between chains, R-hat values were below 1.06 for all program-specific outcome estimates.

E.4. TECHNICAL DISCUSSION OF FITTED MODELS UNDERLYING LOCAL ESTIMATES

This section presents the numeric diagnostic summaries and plots of priors and posteriors for key parameters, the random effect variance, and one of the regressors, by outcome.

The prior distribution for regression coefficients was double exponential / Laplace which has a sharp peak at zero and tails heavier than the normal distribution. This prior distribution was chosen because the posterior mode in regression models corresponds to the frequentist lasso estimate. The prior distributions of the random effect variances were half-Cauchy, i.e., the positive values of the Cauchy distribution with the location parameter of zero and scale parameter of 1. Random effect variance directly address the issue of variability of outcome rates, i.e., Research Question 8. However, if the random effect models cannot extract information concerning this variability, then this Research Question can scarcely be answered. Hence we hope to see that the posterior distribution is much more concentrated than the prior distribution. Graphical displays will also be supplemented by Bayesian computing diagnostics to ensure that we can appropriately interpret the results. For both types of parameters, we hope to see that the posterior is more concentrated that the prior.

E.4.1 PROGRAM COMPLETION

The following Bayesian summaries apply to the random effect standard deviation parameter τ:

- Posterior mean = 1.15
- Posterior standard deviation = 0.18
- 95% highest posterior density credible interval = (0.85; 1.55)
- Potential scale reduction factor Rho = 1.00
- Effective sample size = 7,196 (out of 12,000)

Exhibit E-5 displays autocorrelations for estimates of τ by lags between draws. There is one panel for each of the first five chains. The other chains performed similarly. Note that the auto correlation for lag=1 (consecutive draws) is about 0.1 and climbs slightly for lag=2 for some unknown reason. Autocorrelations for lag=3 and higher is near zero, which is a good thing.

Exhibit E-5. Autocorrelation in Estimates of Between-Program Standard Deviation in Program Completion Rate by Lag

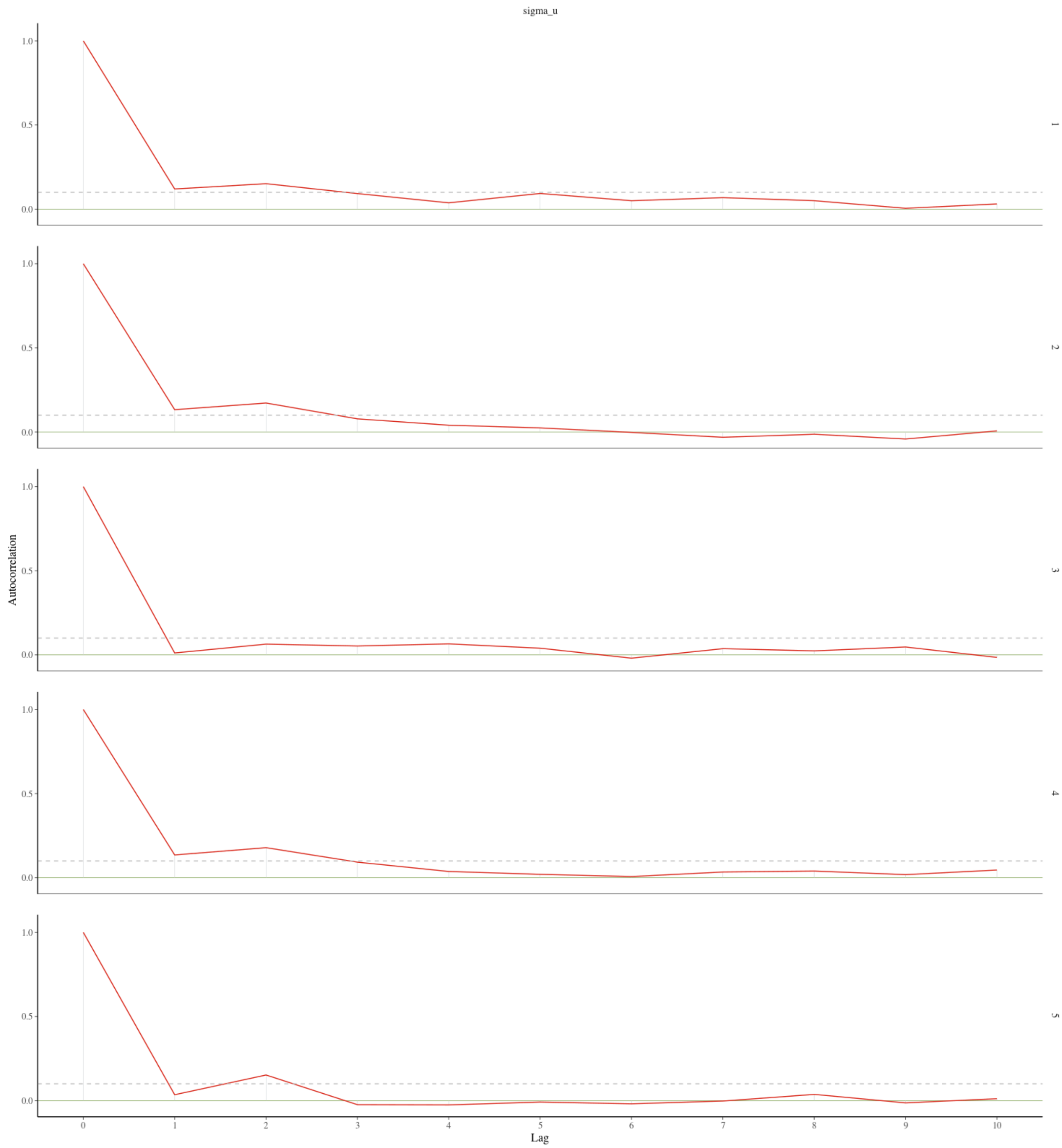


Exhibit E-6 displays both the prior and posterior densities for the between-program standard deviation in the program completion rate. This is the critical parameter that governs the degree of shrinkage. The dashed line shows the half-Cauchy distribution used as the prior distribution. It has the highest density at $\tau = 0$, and a very gradually declining density for larger values. The solid line shows the posterior distribution. Note the sharp peak at about $\tau = 1.2$ and note how the density fall to zero for $\tau < 0.7$ and for $\tau > 1.8$. This indicates that the observed data support the belief that there is very large variation in program completion rates even after accounting for student profiles and program duration. (Recall that this standard deviation is on the logit scale, so a value of 1.2 is very large.) Because of this large value for τ, the Bayesian procedure estimated program-specific program completion rates very similar to those estimated by the design-based frequentist method, as shown in **Exhibit E-1**.

Exhibit E-6. Overlaid Prior and Posterior Densities for Between-Program Standard Deviation in Program Completion Rate

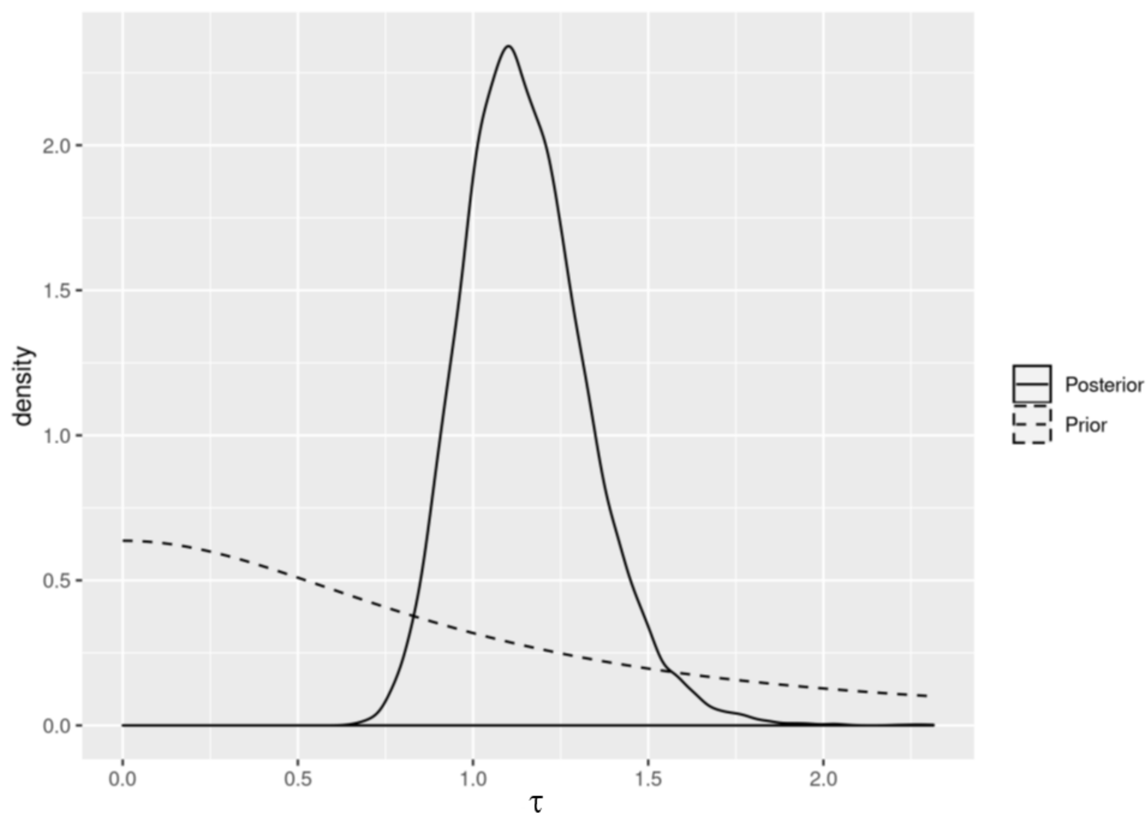
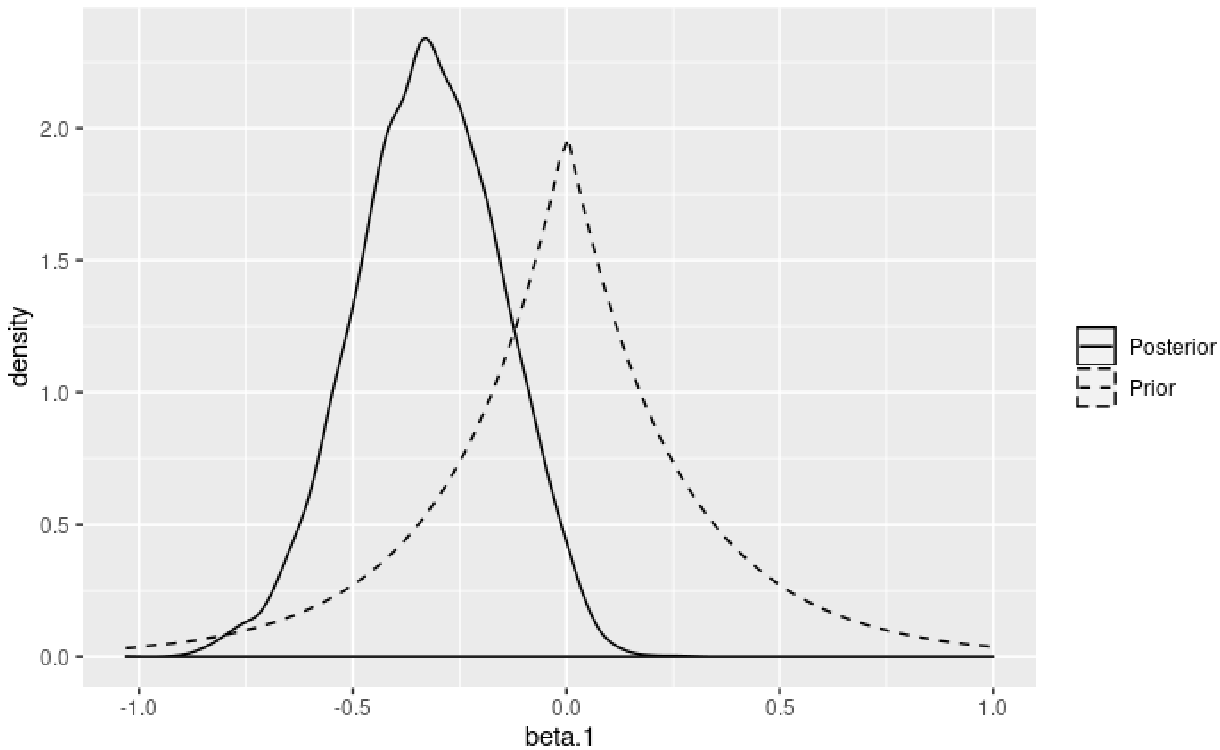


Exhibit E-7 shows a similar prior-vs-posterior graph for the effect of being under age 21 on the logit probability of program completion. (There is nothing special about this particular variable—it was picked merely for illustrative purposes.) Prior vs. posterior plot shows that the prior is strongly informative, as the posterior has about the same height and spread as the prior. However the information contained in the data shifted the distribution; the parameter can be considered "significant" since the 95% credible interval does not cover zero.

Exhibit E-7. Overlaid Prior and Posterior Densities for Effect of Being under Age 21 on Program Completion Rate



E.4.2 TRAINING-RELATED EMPLOYMENT

The following Bayesian summaries apply to the random effect standard deviation parameter τ:

- Posterior mean = 0.98
- Posterior standard deviation = 0.17
- 95% highest posterior density credible interval = (0.70; 1.37)
- Potential scale reduction factor Rho = 1.01
- Effective sample size = 5,246 (out of 12,000)

Exhibit E-8 displays both the prior and posterior densities for the between-program standard deviation in the training-related employment rate. This is the critical parameter that governs the degree of shrinkage. The dashed line shows the half-Cauchy distribution used as the prior distribution. It has the highest density at $\tau = 0$, and a very gradually declining density for larger values. The solid line shows the posterior distribution. Note the sharp peak at about $\tau = 0.85$ and note how the density fall to zero for $\tau < 0.5$ and for $\tau > 1.7$. This indicates that the observed data support the belief that there is very large variation in training-related employment rates even after accounting for student profiles and program duration. This is a bit smaller than for program completion, but still very large. Because of this large value for τ, the Bayesian procedure estimated program-specific training-related employment rates very similar to those estimated by the design-based frequentist method, as shown in **Exhibit E-2**.

Exhibit E-8. Overlaid Prior and Posterior Densities for Between-Program Standard Deviation in Training-Related Employment Rate

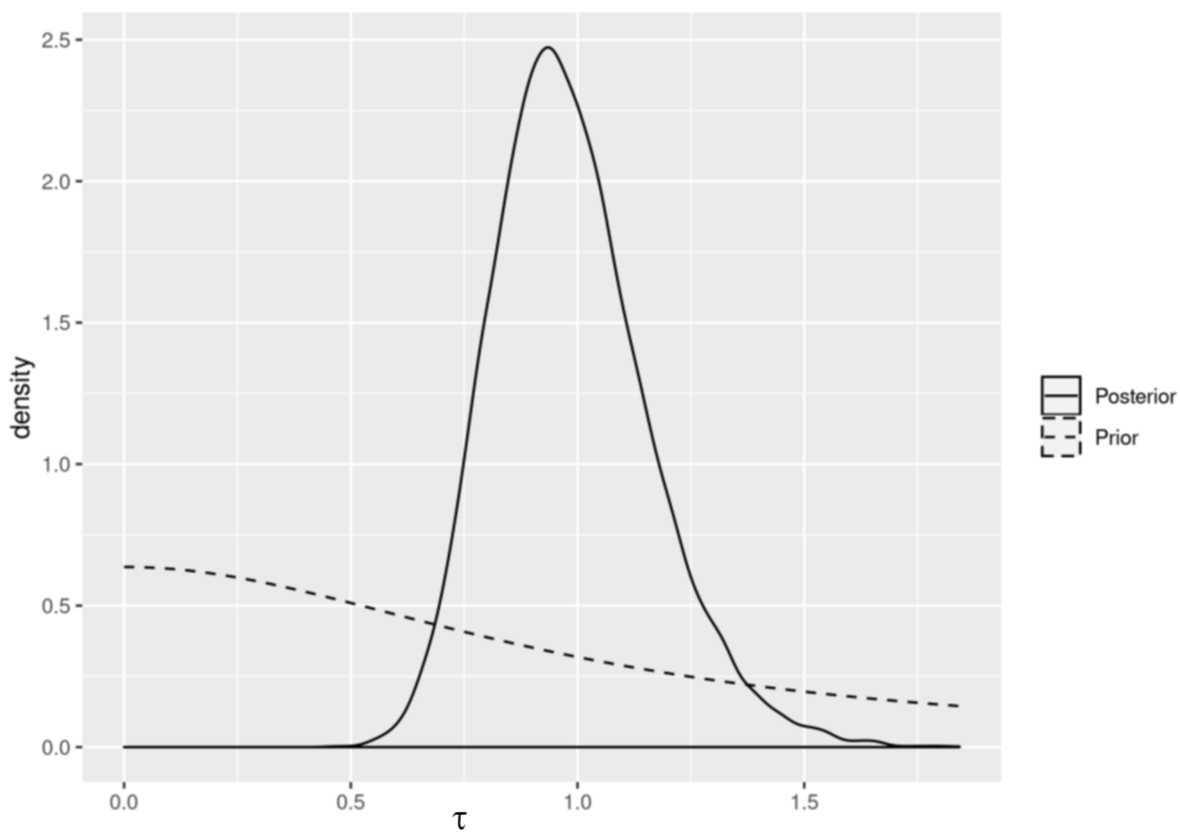
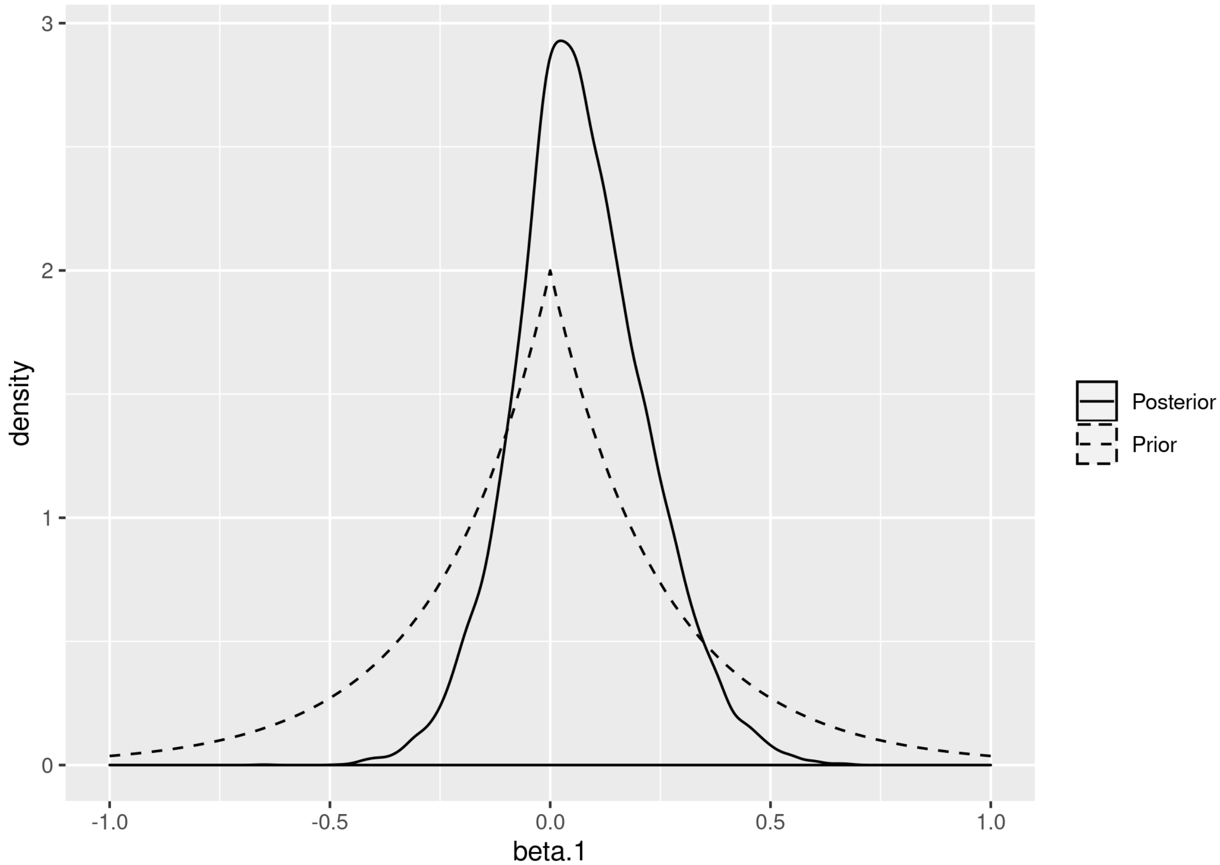


Exhibit E-9 shows a prior-vs-posterior plot for the effect of being under age 21 on the logit probability of job alignment. Prior vs. posterior plot shows that the prior is strongly informative, as the posterior has about the same height and spread as the prior. Information added by the data is not sufficient to move the posterior distribution away from zero.

Exhibit E-9. Overlaid Prior and Posterior Densities for Effect of Being under Age 21 on Training-Related Employment Rate



E.4.3 PUBLIC ASSISTANCE BENEFITS RECEIPT

The following Bayesian summaries apply to the random effect standard deviation parameter τ:

- Posterior mean = 0.17
- Posterior standard deviation = 0.11
- 95% highest posterior density credible interval = (0.01; 0.41)
- Potential scale reduction factor Rho = 1.11
- Effective sample size = 97 (out of 12,000)

Convergence was less than satisfactory for this parameter. However, this is not particularly problematic for interpretation of Bayesian estimates, since the estimate itself is small. This in turn is due to high explanatory power of fixed effects that used receipt of public assistance at baseline as predictors that have very strong explanatory power: the coefficient for receipt of SNAP has a 95% posterior interval of (1.62, 2.33), and receipt of TRA, (0.49, 2.04). We alluded to this situation in our explanation of the allocation of the explanatory power within the statistical model: once most of the variability of outcomes is explained by the fixed effects portion of the model, the residual variance to be explained is small and more difficult to identify.

Exhibit E-10 displays both the prior and posterior densities for the between-program standard deviation in the public assistance benefits receipt rate. This is the critical parameter that governs the degree of shrinkage. The dashed line shows the half-Cauchy distribution used as the prior distribution. It has the highest density at τ =0, and a very gradually declining density for larger values. The solid line shows the posterior distribution. Note that this posterior distribution is not as sharply peaked as those in **Exhibits E-6**, **E-8**, and **E-9**. There is an apparent accumulation of density at τ =0. A value of zero would indicate that there is no idiosyncratic variation in this outcome after controlling for the student profile, program duration, and the local employment rate. But fairly large values of τ cannot be ruled out. All in all, it appears that the data on this outcome provide less information for estimation of the τ parameter than for other outcomes, as evidenced by a low effective sample size (not shown). Because of the small value for τ, the Bayesian procedure estimated program-specific public assistance receipt rates are very different from those estimated by the design-based frequentist method, as shown in **Exhibit E-4**.

Exhibit E-10. Overlaid Prior and Posterior Densities for Between-Program Standard Deviation in Rate of Public Assistance Benefits Receipt

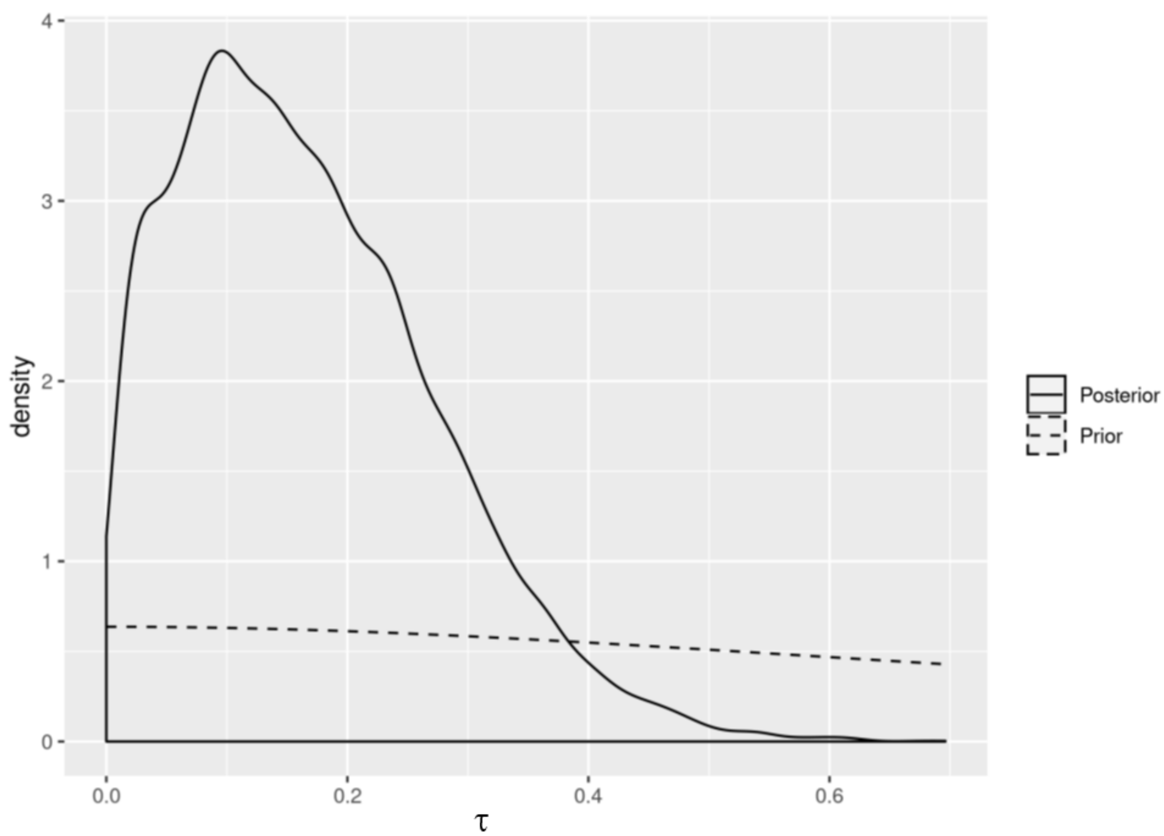
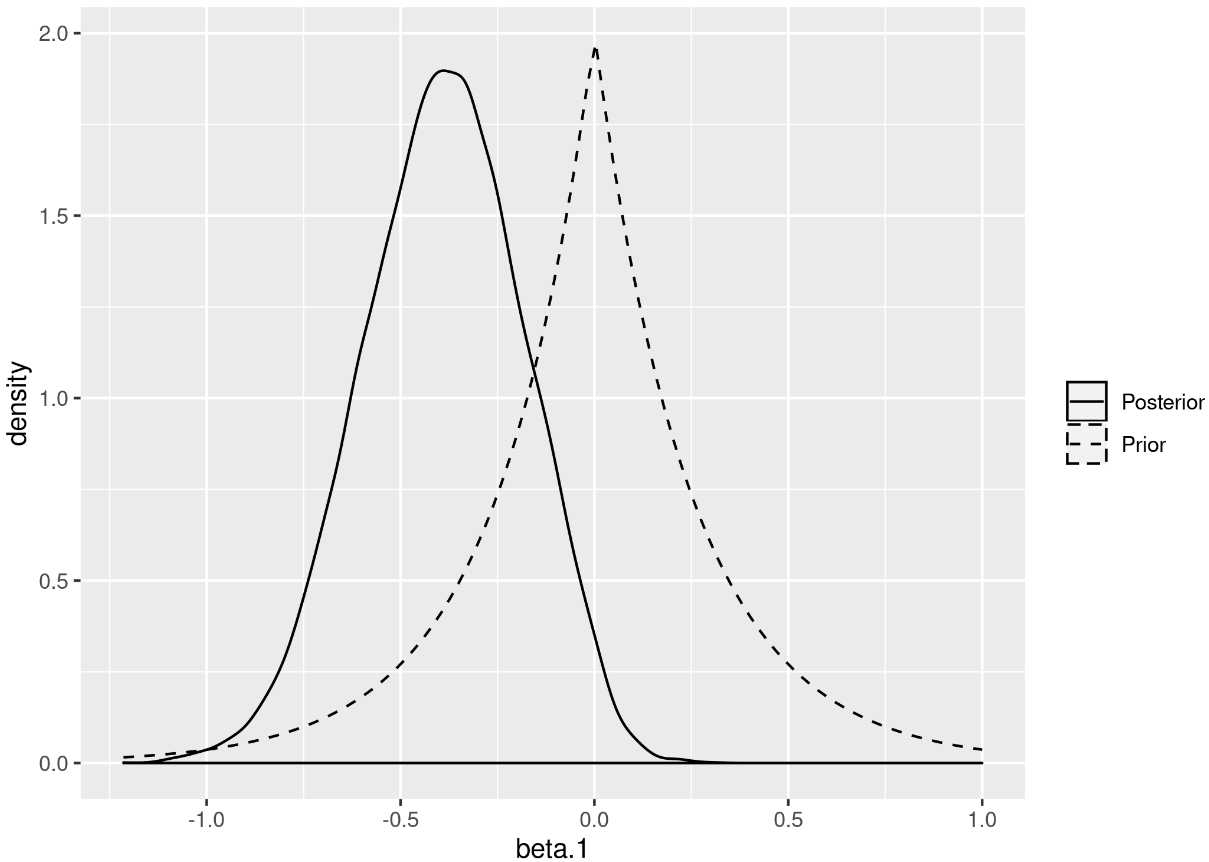


Exhibit E-11 shows a prior-vs-posterior plot for the effect of being under age 21 on the inverse logit probability of public assistance benefits receipt. Prior vs. posterior plot shows that the prior is strongly informative, as the posterior has about the same height and spread as the prior. The estimate is "significant" as the 95% highest posterior density credible interval (-0.805, -0.013) is isolated from zero.

Exhibit E-11. Overlaid Prior and Posterior Densities for Effect of Being under Age 21 on Rate of Public Assistance Benefits Receipt



E.4.4 CHANGE IN EARNINGS

The following Bayesian summaries apply to the random effect standard deviation parameter τ:

- Posterior mean = \$599
- Posterior standard deviation = \$278
- 95% highest posterior density credible interval = (\$78.67, \$1,210)
- Potential scale reduction factor Rho = 1.04
- Effective sample size = 313 (out of 12,000)

Convergence was less than ideal for this parameter. As was the case for the public assistance receipt, reduction in the explained variability in the outcome is driven by the explanatory variables in the outcome regression, with e.g. the age predictors and program duration having strong significant effects: age 20 or less, 95% posterior credible interval of ($1,123; $2,593); age 21 to 24, 95% posterior credible interval of ($15; $1,348); program length in years, 95% posterior credible interval of ($409; $2,322).

Exhibit E-12 displays both the prior and posterior densities for the between-program standard deviation in the change in earnings. The dashed line shows the half-Cauchy distribution used as the prior distribution. The data shifts the distribution very significantly. Between-program variability is lower than both the effects of the strongest predictors quoted in the preceding paragraph, and residual variability (**Exhibit E-13**) which is about 5 times greater, and has a 95% posterior credible interval of ($2,390; $2,744).

Exhibit E-12. Overlaid Prior and Posterior Densities for Between-Program Standard Deviation in Change in Earnings

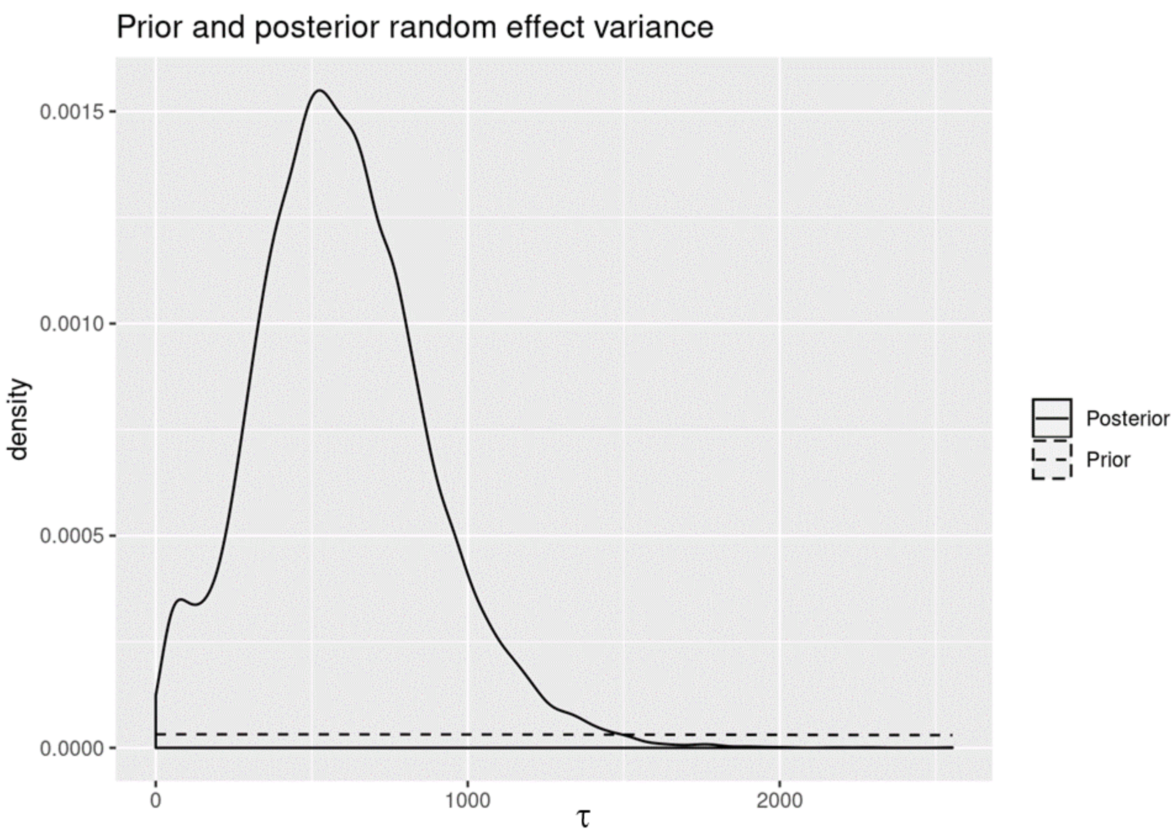


Exhibit E-13. Overlaid Prior and Posterior Densities for Residual Standard Deviation in Change in Earnings

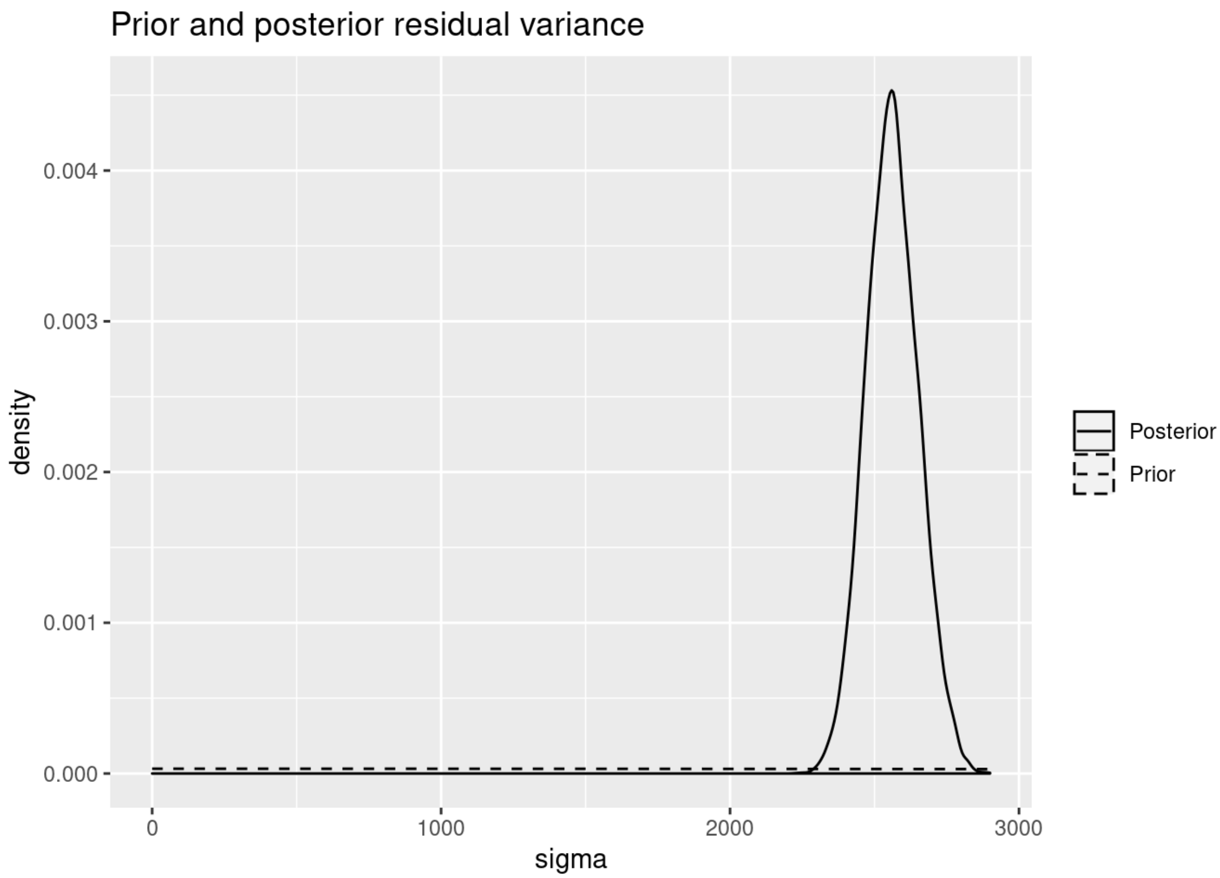
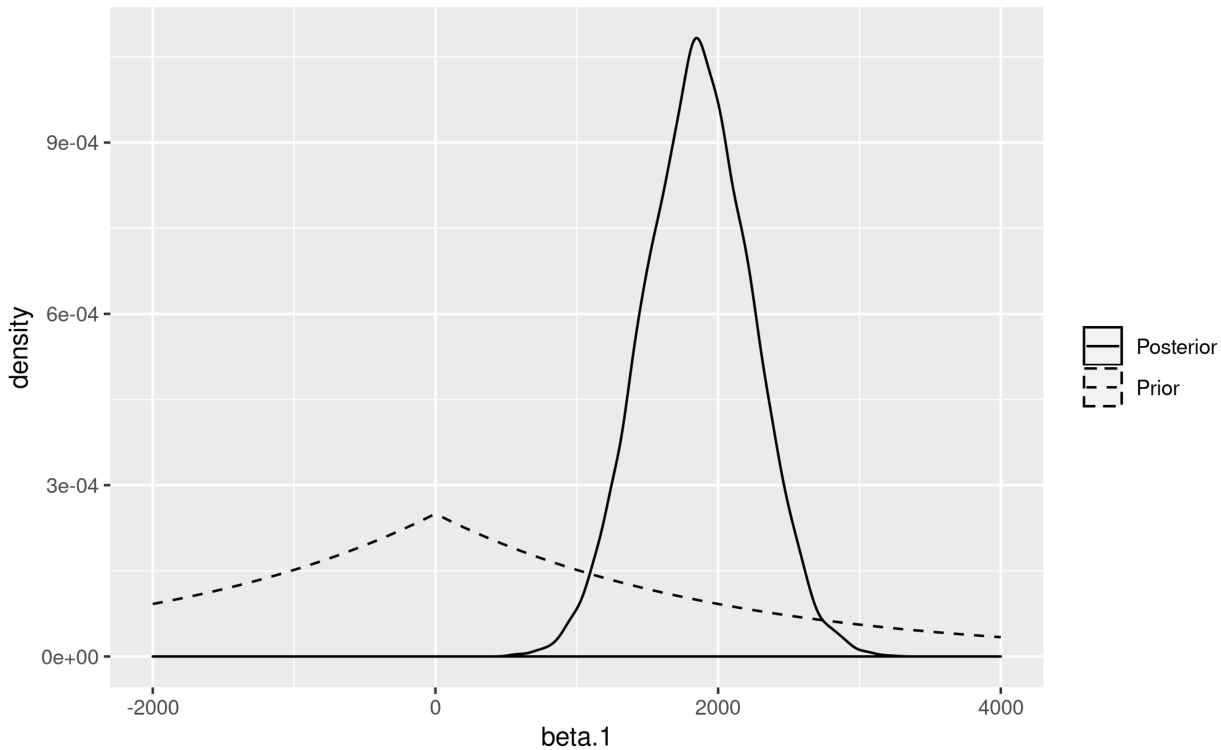


Exhibit E-14 shows a prior-vs-posterior plot for the effect of being under age 21 on the change in earnings. Prior vs. posterior plot shows that the prior is weakly informative, as it has lower height and greater spread compared to the posterior, but is still noticeable unlike say the prior in **Exhibit E-13**. The estimate is "significant" as the 95% highest posterior density credible interval ($1,123; $2,593) is isolated from zero.

Exhibit E-14. Overlaid Prior and Posterior Densities for Effect of Being under Age 21 on Change in Earnings



F. Implementation Data Collection

This appendix describes implementation data collection. Section F.1 discusses the site visits conducted by the research team and Section F.2 describes how the site visit data were analyzed.

F.1. SITE VISITS

The research team conducted site visits to the nine outcome study grantees in March and April 2017. The site visits were designed to inform the outcomes study analysis, documenting participant experiences in the training programs and grantees' implementation of capacity-building activities. The site visits were intended to contextualize findings from the outcomes study.

The research team's site visitors worked with grant staff to schedule the site visits.[13] Site visitors typically worked with the grant director to set site visit dates and to develop an agenda for the visit, including the colleges and campuses to be visited and staff to be interviewed. The length of the visits varied from one grantee to the next based on the number of programs that were included in the outcomes study and the number of colleges (for consortiums) and campuses (for consortiums and single institution grantees) to be visited. In some cases, it was not possible to visit each college or campus. In those situations, site visitors prioritized visiting colleges with several programs in the outcomes study over colleges that had only one program in the study. If multiple colleges in a consortium were offering similar versions of the same program, the site visitors visited a subset of the colleges.

Site visitors conducted semi-structured interviews with four types of stakeholders: college leadership, grant directors, key partners and employers, and faculty and staff.[14] Interviews typically lasted between one and one and a half hours. Site visitors took verbatim notes and made audio recordings of the interviews. Interview guides were designed to collect data on the grant's institutional context; planning and initial implementation; recruitment; key components of training programs; capacity-building activities; partnerships and systems alignment efforts; and post-grant plans and sustainability.

The research team also toured renovated training facilities and classrooms. When possible, the team attended a session of the training programs and took notes in an observation tool. The observation tool captured data on the setting and physical environment, content of the session, teaching methods, participant engagement, participant-instructor rapport, and participant relationships.

After each site visit, site visitors reviewed their notes to clarify any ambiguities and resolve typos or other errors. Site visitors then developed a report to summarize key findings.

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[13] Site visitors consisted of one senior and one junior member of the research team. The senior member led the interviews and the junior member scheduled the visit, planned logistics, and took notes. Two site visit teams visited the Chaffey College consortium and Ivy Tech College because both grantees had multiple colleges or campuses and many training programs included in the outcomes study.

[14] Interview guides can be found at https://www.reginfo.gov/public/do/PRAICList?ref_nbr=201505-1291-001.

F.2. ANALYSIS

The research team developed a set of spreadsheets to capture and analyze information from the site visit reports. The categories in the spreadsheet corresponded to the topics that are highlighted in the final report. The categories were accelerated and enhanced learning, persistence and completion, connections to employment, partnerships, successes and challenges, and sustainability. The research team reviewed and analyzed the tables, noting themes that emerged across the site visits and highlighting examples of illustrative activities and practices. This process of review and analysis formed the basis for the material included in the report.

G. Expanded Results

This appendix provides expanded results for the analyses presented in Chapters 4 through 7 of this report.

G.1. EXPANDED RESULTS FOR CHAPTER 4

Exhibit G-1 contains expanded results of the participant characteristics reported at program entry, including the mean and 95 percent confidence interval for each measure.

Exhibit G-1. Expanded Results, Participant Characteristics at Program Entry

Characteristic	Mean	95% Confidence Interval	Sample Size
Age (%)			
20 or younger	23.0	(17.4, 28.6)	2,767
21 to 24	17.5	(15.4, 19.6)	2,767
25 to 34	30.2	(27.6, 32.8)	2,767
35 or older	29.4	(24.3, 34.5)	2,767
Gender (%)			
Male	85.4	(79.8, 91.0)	2,767
Female	14.6	(9.0, 20.2)	2,767
Race/Ethnicity (%)			
Hispanic, any race	21.6	(12.6, 30.5)	2,767
White (Non-Hispanic)	47.7	(36.1, 59.2)	2,767
Black (Non-Hispanic)	22.5	(10.2, 34.8)	2,767
Asian (Non-Hispanic)	4.2	(2.6, 5.8)	2,767
Other, including multi-race (Non-Hispanic)	4.0	(3.3, 4.8)	2,767
Family Structure (%)			
No spouse/partner, no child	56.0	(51.6, 60.3)	2,767
No spouse/partner, has children	14.2	(11.8, 16.7)	2,767
Has spouse/partner, no children	13.4	(12.1, 14.8)	2,767
Has spouse/partner, has children	16.4	(13.0, 19.8)	2,767
Education Attainment (%)			
Less than high school	4.1	(2.0, 6.1)	2,767
High school or GED	42.8	(37.3, 48.3)	2,767
Technical or vocational degree	6.0	(4.8, 7.3)	2,767
Some college but no degree	32.0	(28.6, 35.3)	2,767
Associate's degree	7.4	(5.7, 9.1)	2,767
Bachelor's degree or more	7.7	(5.5, 10.0)	2,767
Family Income in past 12 months (%)			
$0 - $14,999	30.3	(25.0, 35.6)	2,767
$15,000 - $29,999	27.6	(25.3, 29.9)	2,767
$30,000+	42.1	(36.5, 47.7)	2,767
Housing (%)			
Own the place where you live	17.9	(15.6, 20.2)	2,767
Rent own place or contribute to rent at friend or family's place	53.2	(49.1, 57.2)	2,767
Live rent free	28.9	(25.2, 32.6)	2,767

Characteristic	Mean	95% Confidence Interval	Sample Size
Public Assistance (%)			
Currently receiving TRA	1.6	(0.7, 2.5)	2,767
Currently receiving SNAP	11.5	(8.3, 14.6)	2,767
Currently receiving TANF	1.6	(0.8, 2.4)	2,767
Currently receiving TANF or SNAP	11.8	(8.6, 15.0)	2,767
Currently receiving UI	5.3	(2.7, 7.9)	2,767
Employment Status (%)			
Currently working	56.4	(51.8, 60.9)	2,767
Not currently working, but worked at some point during the past 12 months	29.8	(25.5, 34.1)	2,767
Not currently working, longer than 12 months since last worked	10.2	(8.1, 12.3)	2,767
Never worked	3.7	(3.0, 4.4)	2,767
Expected Work Hours (%)			
0	22.4	(18.5, 26.3)	2,767
1 to 19	7.3	(5.0, 9.7)	2,767
20 to 34	23.1	(18.9, 27.2)	2,767
35 and plus	47.2	(38.8, 55.5)	2,767
Citizenship and Veteran Status (%)			
Citizen and veteran	8.9	(6.9, 10.9)	2,767
Citizen, not veteran	84.5	(81.9, 87.1)	2,767
Not citizen	6.6	(4.2, 8.9)	2,767
Language (%)			
Speak English at home	74.2	(66.7, 81.7)	2,767
Speak language other than English at home	25.8	(18.3, 33.3)	2,767
Expected Program Participation (%)			
Expect to participate full time	59.5	(48.4, 70.6)	2,767
Expect to participate part time	40.5	(29.4, 51.6)	2,767
Most Important Reasons to Participate (%)			
Find Work	19.5	(16.5, 22.6)	2,767
Career Change	25.2	(21.9, 28.5)	2,767
Career Advancement	29.2	(25.0, 33.4)	
Education Advancement	14.4	(11.7, 17.2)	2,767
Personal Reasons	8.3	(7.0, 9.7)	2,767
Others	3.4	(2.6, 4.2)	2,767
Prior Experience in Industry (%)			
None	60.4	(54.5, 66.2)	2,767
Some but less than one year	6.0	(4.8, 7.1)	2,767
One year or more	33.7	(28.2, 39.2)	2,767
Training Duration (%)			
Greater than one semester	45.7		2,767
Household Income below Poverty Line (%)			
Household is below poverty level	42.5	(37.0, 48.1)	2,767

Exhibits G.2 to **G.5** contains expanded results of the outcomes reported in Chapter 4, including training duration, service receipt, training, and employment, earnings, and income.

Exhibit G-2. Expanded Results, Training Duration Outcomes

Outcome	Mean	95% Confidence Interval	Sample Size
Training duration, full sample			
Total months of training	7.4	(6.5, 8.3)	2,211
FTE months of training	6.2	(5.4, 7.0)	2,211
More than 6 FTE months of training (%)	44.2	(34.2, 54.3)	2,211
Training duration, among those who finished classes			
Total months of training	6.2	(5.2, 7.2)	1,313
FTE months of training	5.5	(4.4, 6.6)	1,313
Six or more FTE months of training (%)	38.8	(23.9, 53.8)	1,313

Exhibit G-3. Expanded Results, Service Receipt Outcomes

Outcome	Mean	95% Confidence Interval	Sample Size
Accelerated Learning (%)			
Received transfer credits earned from previous college	20.7	(13.9, 27.5)	2,211
Number of transfer credits received	5.6	(4.0, 7.1)	459
Received transfer credits earned from prior learning	4.4	(3.2, 5.5)	2,211
Number of prior learning or work experience credits received	1.4	(0.9, 2.0)	95
Stated there is a recommended program leading to next level credential	69.1	(61.5, 76.7)	2,211
Completion and Persistence (%)			
Attended course focusing on study skills, workplace skills, or general life skills	45.5	(40.5, 50.6)	2,211
Ever took career planning course	22.1	(18.2, 26.0)	2,211
Ever took course about study skills	23.6	(19.5, 27.6)	2,211
Ever took a course about job search	20.7	(17.2, 24.2)	2,211
Ever took a course about critical thinking and problem solving	27.5	(23.7, 31.2)	2,211
Ever took a course about finding help with life problems	19.0	(15.8, 22.2)	2,211
Ever took a course about financial aid for school	15.8	(12.4, 19.3)	2,211
Ever took a course about time management	22.0	(18.5, 25.6)	2,211
Ever took a course about working in groups	24.6	(20.7, 28.6)	2,211
Ever took a course about communicating well	26.2	(21.8, 30.6)	2,211
Ever took a course about managing stress and anger	11.0	(8.2, 13.8)	2,211
Ever took a course about staying motivated	21.9	(17.9, 25.8)	2,211
Ever took a course about acting professionally	28.6	(24.1, 33.0)	2,211
Ever took a course about managing finances	9.9	(6.5, 13.3)	2,211
Ever took a course about handling family responsibilities	8.0	(5.4, 10.6)	2,211
Received academic advising	47.8	(40.4, 55.1)	2,211
Received financial aid advising	31.8	(24.3, 39.4)	2,211

Outcome	Mean	95% Confidence Interval	Sample Size
Sources of Financial Assistance for Training Programs (%)			
Own earnings or savings or those of a spouse	49.5	(45.6, 53.4)	2,211
Loans in own name or name of a family member	21.0	(13.5, 28.5)	2,211
A parent or other family member	25.4	(21.4, 29.4)	2,211
Grant from the government	38.8	(31.6, 46.1)	2,211
Used TRA benefits to pay for training costs	7.6	(4.1, 11.2)	2,211
Veteran's benefits	5.2	(3.4, 7.0)	2,211
Scholarship	14.4	(9.1, 19.8)	2,211
Financial support from employer	9.2	(6.1, 12.2)	2,211
Other funding source	15.6	(13.0, 18.2)	2,211
Work-based Learning (%)			
Coursework utilized virtual workplace simulations to practice	48.0	(38.2, 57.8)	2,211
Coursework utilized work-like physical environments to practice	80.8	(76.0, 85.6)	2,211
Offered arranged visits from employer/learning about employers	51.4	(43.2, 59.6)	2,211
Offered class taught by instructors from local employer/class	35.3	(30.3, 40.2)	2,211
Opportunity for work study job or internship	56.7	(47.4, 66.1)	2,211
Offered a work study job as part of studies	26.8	(19.7, 34.0)	2,211
Offered clinical experience or practicum as part of studies	21.7	(14.3, 29.1)	2,211
Offered an apprenticeship as part of studies	22.1	(15.2, 28.9)	2,211
Offered an internship as part of studies	25.0	(14.2, 35.8)	2,211
Offered other work experience as part of studies	29.5	(25.0, 34.1)	2,211
Received career counseling	34.8	(30.7, 38.9)	2,211
Received job search or placement assistance	39.5	(31.2, 47.8)	2,211
Create or edit a resume	32.8	(24.7, 40.9)	2,211
Look for a job	33.3	(25.5, 41.2)	2,211
Use web-based search engines	23.0	(17.5, 28.5)	2,211
Find specific job leads	29.8	(22.7, 37.0)	2,211
Fill out job applications	20.3	(15.5, 25.2)	2,211
Opportunity for coached job interview practice	25.4	(18.1, 32.7)	2,211
Academic Advising (%)			
Only college provided academic advising	90.0	(87.0, 93.0)	1,058
Only other organization provided academic advising	4.0	(2.2, 5.9)	1,058
Both college and other organization provided academic advising	6.0	(4.2, 7.7)	1,058
Financial Aid Advising (%)			
Only college provided financial advising	87.1	(83.8, 90.4)	696
Only other organization provided financial advising	6.1	(3.4, 8.8)	696
Both college and other organization provided financial advising	6.8	(4.4, 9.1)	696

Outcome	Mean	95% Confidence Interval	Sample Size
Career Counseling (%)			
Only college provided career counseling	85.2	(81.4, 89.0)	768
Only other organization provided career counseling	5.3	(3.0, 7.5)	768
Both college and other organization provided career counseling	9.6	(6.8, 12.3)	768
Job Search Assistance (%)			
Only college provided job search assistance	79.2	(72.2, 86.2)	872
Only other organization provided job search assistance	7.3	(2.7, 11.8)	872
Both college and other organization provided job search assist	13.5	(9.7, 17.3)	872
Resume Help (%)			
Only college provided resume help	78.6	(72.3, 84.9)	722
Only other organization provided resume help	5.5	(1.9, 9.1)	722
Both college and other organization provided resume help	15.9	(11.8, 19.9)	722
Job Search Training (%)			
Only college provided help on how to look for job	74.2	(69.0, 79.5)	735
Only other organization provided help on how to look for job	4.3	(1.5, 7.2)	735
Both college and other organization provided help on how to look for job	21.4	(17.7, 25.1)	735
Job Search using Search Engine (%)			
Only college provided help using job search engines	75.5	(69.7, 81.4)	507
Only other organization provided help using job search engines	6.3	(2.6, 10.0)	507
Both college and other organization help using job search engines	18.2	(14.7, 21.6)	507
Finding Specific Job Leads (%)			
Only college provided help finding specific job leads	76.0	(70.1, 81.9)	657
Only other organization provided help finding specific job leads	4.8	(1.9, 7.7)	657
Both college and other organization help finding specific job leads	19.2	(14.7, 23.7)	657
Job Applications (%)			
Only college provided help filling out job applications	73.3	(64.6, 82.1)	445
Only other organization provided help filling out job applications	7.8	(2.4, 13.2)	445
Both college and other organization help filling out job applications	18.9	(13.7, 24.0)	445
Job Interviews (%)			
Only college provided help practicing for job interviews	78.3	(71.2, 85.4)	557
Only other organization provided help practicing for job interviews	7.2	(2.4, 12.0)	557
Both college and other organization help practicing for job interviews	14.5	(10.5, 18.5)	557

Outcome	Mean	95% Confidence Interval	Sample Size
Satisfaction with Program (%)			
Very satisfied with program	59.8	(55.6, 64.0)	2,211
Somewhat satisfied with program	32.8	(29.1, 36.6)	2,211
Not satisfied with program	7.5	(6.2, 8.8)	2,211

Exhibit G-4. Expanded Results, Training Outcomes

Outcome	Mean	95% Confidence Interval	Sample Size
Finished Classes (%)	59.4	(49.9, 68.8)	2,211
Left without Finishing Classes (%)	23.5	(18.7, 28.4)	2,211
Still Enrolled in Required Classes at Follow-up (%)	17.1	(10.6, 23.6)	2,211
Credential (%)			
Finished classes and received any credential	51.4	(40.8, 61.9)	2,211
Finished classes and received target credential	28.7	(18.1, 39.4)	2,211
Additional Training (%)			
Finished classes and started additional training	16.6	(11.5, 21.7)	2,211
Finished classes, received any credential, and started additional training	14.4	(9.4, 19.4)	2,211
Finished classes, received target credential, and started additional training	8.1	(3.6, 12.6)	2,211
Return to College (%)			
Plan to return to college	52.1	(48.1, 56.1)	2,211
Plan to return to college, completed program	26.1	(19.5, 32.7)	2,211
Plan to return to college, still enrolled in program	10.9	(6.8, 15.0)	2,211
Plan to return to college, left program	15.1	(11.3, 18.9)	2,211
Number of months until planning to return to college	8.3	(6.9, 9.7)	1,154
College Credits (%)			
Earning college credits	32.2	(20.8, 43.6)	2,211
Total college credits earned since beginning program	16.9	(13.4, 20.4)	711

Exhibit G-5. Expanded Results, Employment, Earnings, and Income Outcomes

Outcome	Mean	95% Confidence Interval	Sample Size
Employment (%)			
Employed in 7th quarter before program entry	63.0	(58.8, 67.3)	1,845
Employed in 6th quarter before program entry	64.1	(60.3, 67.8)	2,355
Employed in 5th quarter before program entry	66.1	(62.0, 70.2)	2,355
Employed in 4th quarter before program entry	68.1	(63.7, 72.5)	2,355
Employed in 3rd quarter before program entry	71.1	(67.3, 74.9)	2,355
Employed in 2nd quarter before program entry	70.6	(67.1, 74.1)	2,355
Employed in 1st quarter before program entry	71.3	(67.6, 75.1)	2,355
Employed in quarter of program entry	66.2	(61.7, 70.6)	2,355
Employed in 1st quarter after program entry	69.3	(65.4, 73.2)	2,355
Employed in 2nd quarter after program entry	75.0	(71.8, 78.2)	2,355
Employed in 3rd quarter after program entry	77.8	(74.2, 81.5)	2,355
Employed in 4th quarter after program entry	76.4	(71.2, 81.7)	2,355
Employed in 5th quarter after program entry	77.5	(73.3, 81.8)	2,355
Number of quarters employed between 1st and 5th quarters (range 0 to 5)	3.76	(3.59, 3.93)	2,355
Earnings ($)			
Earnings in 7th quarter before program entry	4,276	(3,786, 4,766)	1,845
Earnings in 6th quarter before program entry	4,155	(3,655, 4,656)	2,355
Earnings in 5th quarter before program entry	4,434	(3,894, 4,974)	2,355
Earnings in 4th quarter before program entry	4,787	(4,203, 5,372)	2,355
Earnings in 3rd quarter before program entry	4,915	(4,304, 5,526)	2,355
Earnings in 2nd quarter before program entry	5,099	(4,465, 5,733)	2,355
Earnings in 1st quarter before program entry	4,888	(4,132, 5,645)	2,355
Earnings in quarter of program entry	4,452	(3,638, 5,266)	2,355
Earnings in 1st quarter after program entry	4,602	(3,776, 5,428)	2,355
Earnings in 2nd quarter after program entry	5,420	(4,650, 6,191)	2,355
Earnings in 3rd quarter after program entry	6,149	(5,374, 6,924)	2,355
Earnings in 4th quarter after program entry	6,750	(5,682, 7,819)	2,355
Earnings in 5th quarter after program entry	7,187	(6,136, 8,238)	2,355
Earnings ($), among those employed in a job related to training			
Earnings in 7th quarter before program entry	5,363	(4,591, 6,135)	371
Earnings in 6th quarter before program entry	5,446	(4,686, 6,207)	459
Earnings in 5th quarter before program entry	5,808	(4,874, 6,743)	459
Earnings in 4th quarter before program entry	5,866	(4,864, 6,869)	459
Earnings in 3rd quarter before program entry	6,038	(4,942, 7,135)	459
Earnings in 2nd quarter before program entry	6,100	(5,173, 7,028)	459
Earnings in 1st quarter before program entry	5,601	(4,738, 6,464)	459
Earnings in quarter of program entry	4,694	(3,453, 5,935)	459
Earnings in 1st quarter after program entry	4,638	(3,195, 6,081)	459
Earnings in 2nd quarter after program entry	6,057	(4,679, 7,435)	459
Earnings in 3rd quarter after program entry	7,370	(5,983, 8,757)	459
Earnings in 4th quarter after program entry	9,322	(7,707, 10,937)	459
Earnings in 5th quarter after program entry	9,831	(8,168, 11,493)	459

Outcome	Mean	95% Confidence Interval	Sample Size
Earnings ($), among those not employed in a job related to training			
Earnings in 7th quarter before program entry	4,402	(3,797, 5,007)	632
Earnings in 6th quarter before program entry	4,425	(3,826, 5,025)	793
Earnings in 5th quarter before program entry	4,630	(4,056, 5,203)	793
Earnings in 4th quarter before program entry	5,040	(4,409, 5,670)	793
Earnings in 3rd quarter before program entry	5,142	(4,423, 5,861)	793
Earnings in 2nd quarter before program entry	5,326	(4,618, 6,033)	793
Earnings in 1st quarter before program entry	5,156	(4,340, 5,972)	793
Earnings in quarter of program entry	4,953	(4,073, 5,832)	793
Earnings in 1st quarter after program entry	5,289	(4,467, 6,110)	793
Earnings in 2nd quarter after program entry	6,117	(5,237, 6,997)	793
Earnings in 3rd quarter after program entry	6,970	(5,991, 7,949)	793
Earnings in 4th quarter after program entry	7,337	(6,164, 8,510)	793
Earnings in 5th quarter after program entry	8,080	(6,757, 9,403)	793
Earnings of $6,240 or more in 5th quarter after program entry (%)	49.3	(41.4, 57.1)	2,355
Cumulative earnings ($) in the 1st through 5th quarters	30,108	(26,139, 34,077)	2,355
Change of Earnings from 3rd quarter before program entry to 5th quarter after program entry			
Among those who completed program	2,224	(1,431, 3,018)	1,140
Among those who left without completing program	2,715	(1,860, 3,570)	431
Among those who still enrolled in program	1,422	(585, 2,260)	298
Earnings in 5th quarter after program entry			
Among those who completed program	7,472	(6,033, 8,911)	1,140
Among those who left without completing program	7,264	(5,888, 8,639)	431
Among those who still enrolled in program	6,229	(5,284, 7,174)	298
Employment Status (full sample) (%)			
Ever employed after finishing/leaving program	74.5	(68.2, 80.8)	2,211
Currently employed after finishing/leaving program	66.9	(61.3, 72.5)	2,211
Training-Related Employment (full sample) (%)			
Ever employed after finishing/leaving program in a job related to training	29.9	(21.4, 38.3)	2,211
Currently employed after finishing/leaving program in a job related to training	27.3	(19.1, 35.5)	2,211
Ever employed after finishing classes in a job related to training	26.1	(17.9, 34.4)	2,211
Currently employed after finishing classes in a job related to training	24.0	(15.8, 32.1)	2,211
Current Employment (full sample) (%)			
Currently employed full-time	56.4	(50.6, 62.2)	2,211
Currently employed part-time	10.4	(8.8, 12.1)	2,211
Currently underemployed - employed part-time, want to work full-time	7.6	(6.5, 8.8)	2,211
Currently employed part-time, do not want to work full-time	2.8	(1.9, 3.8)	2,211

Outcome	Mean	95% Confidence Interval	Sample Size
Current Employment Benefits (full sample) (%)			
Currently employed in job with health insurance	48.3	(41.6, 55.1)	2,211
Currently employed in job with paid sick days	38.3	(31.2, 45.4)	2,211
Currently employed in job with health insurance and paid sick	35.3	(28.3, 42.4)	2,211
Currently employed in job with paid vacation	45.8	(38.7, 52.9)	2,211
Currently employed in job with paid holidays	45.0	(37.8, 52.3)	2,211
Currently employed in job with retirement or pension benefits	42.3	(35.4, 49.3)	2,211
Reason for Wanting Part-time Work (full sample) (%)			
Child care problems	6.0	(-0.8, 12.8)	63
Other family or personal reasons	51.7	(36.0, 67.4)	63
Health or medical limitation	7.5	(-2.5, 17.6)	63
Retired or Social Security	7.4	(-0.7, 15.5)	63
Satisfied with income from part-time work	29.8	(14.9, 44.7)	63
Employment Status (among those who finished classes) (%)			
Ever employed after finishing classes	90.3	(87.6, 93.0)	1,316
Currently employed after finishing classes	81.8	(77.3, 86.4)	1,316
Training-Related Employment (among those who finished classes) (%)			
Ever employed after finishing classes in a job related to training	44.0	(32.9, 55.2)	1,316
Currently employed after finishing classes in a job related to training	40.4	(28.8, 51.9)	1,316
Current Employment (among those who finished classes) (%)			
Currently employed full-time	71.0	(65.6, 76.5)	1,316
Currently employed part-time	10.8	(8.3, 13.2)	1,316
Currently underemployed - employed part-time, want to work full-time	7.9	(6.4, 9.5)	1,316
Currently employed part-time, do not want to work full-time	2.8	(1.3, 4.4)	1,316
Current Employment Benefits (among those who finished classes) (%)			
Currently employed in job with health insurance	61.3	(52.6, 70.1)	1,316
Currently employed in job with paid sick days	49.5	(40.0, 59.0)	1,316
Currently employed in job with health insurance and paid sick	46.3	(36.8, 55.7)	1,316
Currently employed in job with paid vacation	58.8	(49.4, 68.2)	1,316
Currently employed in job with paid holidays	58.0	(48.5, 67.5)	1,316
Currently employed in job with retirement or pension benefits	54.1	(45.0, 63.2)	1,316
Reason for Wanting Part-time Work (among who finished classes) (%)			
Child care problems	0	N/A	25
Other family or personal reasons	54.8	(32.3, 77.4)	25
Health or medical limitation	10.6	(-1.6, 22.8)	25
Retired or Social Security	11.4	(-3.8, 26.7)	25
Satisfied with income from part-time work	26.7	(4.6, 48.8)	25

Outcome	Mean	95% Confidence Interval	Sample Size
Employment Status (among those who left without completing) (%)			
Ever employed after leaving program	88.7	(86.4, 91.0)	519
Currently employed after leaving program	77.7	(73.8, 81.6)	519
Training-Related Employment (among those who left without completing) (%)			
Ever employed after leaving program in a job related to training	15.9	(12.1, 19.7)	519
Currently employed after leaving program in a job related to training	14.2	(10.9, 17.4)	519
Current Employment (among those who left without completing) (%)			
Currently employed full-time	60.5	(56.2, 64.9)	519
Currently employed part-time	17.2	(14.2, 20.2)	519
Currently underemployed - employed part-time, want to work full-time	12.4	(10.2, 14.5)	519
Currently employed part-time, do not want to work full-time	4.8	(3.1, 6.6)	519
Current Employment Benefits (among those who left without completing) (%)			
Currently employed in job with health insurance	50.6	(45.8, 55.4)	519
Currently employed in job with paid sick days	37.9	(31.2, 44.5)	519
Currently employed in job with health insurance and paid sick	33.5	(27.4, 39.6)	519
Currently employed in job with paid vacation	46.1	(41.6, 50.7)	519
Currently employed in job with paid holidays	45.1	(38.8, 51.3)	519
Currently employed in job with retirement or pension benefits	43.5	(37.2, 49.8)	519
Reason for Wanting Part-time Work (among those who left without completing) (%)			
Child care problems	10.0	(-0.3, 20.3)	38
Other family or personal reasons	49.7	(31.7, 67.7)	38
Health or medical limitation	5.5	(-8.8, 19.7)	38
Retired or Social Security	4.7	(-4.2, 13.6)	38
Satisfied with income from part-time work	31.9	(12.5, 51.4)	38

G.2. EXPANDED RESULTS FOR CHAPTER 5

Exhibits G.6 through **G.9** contain expanded results of the analysis of outcomes by participant characteristics presented in Chapter 5.

Exhibit G-6. Expanded Results for Program Completion by Participant Characteristics

Subgroup	Mean (Group 1)	Mean (Group 2)	Difference	Standard Error	95% Confidence Interval
Male vs. Female (%)	50.1	58.8	-8.7	5.4	(-1.9, 19.4)
Race/ethnicity (%)					
White vs. Hispanic	48.0	52.7	-4.7	6.4	(-17.3, 8.0)
White vs. Black	48.0	59.7	-11.7	9.0	(-29.4, 6.0)
White vs. Other	48.0	45.1	2.9	4.9	(-6.6, 12.4)

Subgroup	Mean (Group 1)	Mean (Group 2)	Difference	Standard Error	95% Confidence Interval
Veteran (%)					
Citizen and veteran vs. Not citizen or veteran	44.1	52.0	-7.9	4.4	(-0.8, 16.6)
Public assistance (%)					
Currently receiving TRA vs. Not currently receiving TRA	58.2	51.2	7.0	6.2	(-19.1, 5.1)
Currently receiving TANF vs. Not currently receiving TANF	64.8	51.1	13.7	11.7	(-36.6, 9.2)
Currently receiving SNAP vs. Not currently receiving SNAP	54.6	50.9	3.7	5.3	(-14.2, 6.8)
Education Attainment (%)					
Less than high school vs. More than high school	46.9	55.3	-8.4	3.1	(2.4, 14.4)
Employment (%)					
Age < 25 currently employed vs. Age <25 work in previous year	43.1	47.3	-4.3	4.4	(-12.8, 4.3)
Age <25 currently employed vs. Age <25 no work in previous year	43.1	40.3	2.8	5.5	(-8.1, 13.6)
Age <25 currently employed vs. Age 25-34 currently employed	43.1	51.6	-8.6	3.6	(-15.7, -1.5)
Age <25 currently employed vs. Age 25-34 work in previous year	43.1	60.9	-17.8	4.3	(-26.3, -9.3)
Age <25 currently employed vs. Age 25-34 no work in previous year	43.1	57.7	-14.6	6.8	(-27.9, -1.3)
Age <25 currently employed vs. Age 35+ currently employed	43.1	54.9	-11.8	5.4	(-22.5, -1.1)
Age <25 currently employed vs. Age 35+ work in previous year	43.1	64.7	-21.6	5.3	(-32.0, -11.2)
Age <25 currently employed vs. Age 35+ no work in previous year	43.1	52.3	-9.2	7.7	(-24.2, 5.8)
Duration (%)					
Greater than one semester vs. One semester or less	41.4	59.9	-18.5	11.2	(-3.4, 40.4)
Previous industry (%)					
Manufacturing vs. Natural resources and mining	54.6	53.0	1.6	10.5	(-19.1, 22.13)
Manufacturing vs. Construction	54.6	64.5	-10.0	6.2	(-22.3, 2.3)
Manufacturing vs. Trade, transportation, utilities	54.6	55.0	-0.5	5.6	(-11.6, 10.6)
Manufacturing vs. Information, finance, professional, business services	54.6	53.0	1.6	6.4	(-10.9, 14.1)
Manufacturing vs. education, health, government	54.6	61.4	-6.8	8.1	(-22.7, 9.1)
Manufacturing vs. Leisure and hospitality	54.6	46.2	8.4	8.2	(-7.8, 24.6)
Manufacturing vs. Other services	54.6	54.4	0.2	7.9	(-15.4, 15.7)

Exhibit G-7. Expanded Results for Training-Related Employment by Participant Characteristic

Subgroup	Mean (Group 1)	Mean (Group 2)	Difference	Standard Error	95% Confidence Interval
Male vs. Female	32.4	35.6	-3.2	12.3	(-20.9, 27.3)
Race/ethnicity					
White vs. Hispanic	35.6	37.3	-1.8	5.1	(-11.8, 8.3)
White vs. Black	35.6	22.1	13.5	4.8	(4.0, 22.9)
White vs. Other	35.6	37.4	-1.8	5.1	(-11.8, 8.2)
Veteran (%)					
Citizen and veteran vs. Not citizen or veteran	30.1	33.2	-3.1	4.5	(-5.6, 11.8)
Public assistance (%)					
Currently receiving TRA vs. Not currently receiving TRA	35.4	32.9	2.5	8.9	(-20.0, 14.9)
Currently receiving TANF vs. Not currently receiving TANF	32.3	32.9	-0.6	9.9	(-18.8, 20.0)
Currently receiving SNAP vs. Not currently receiving TANF	21.8	34.4	-12.6	3.9	(5.0, 20.2)
Education Attainment (%)					
Less than high school vs. More than high school	28.1	37.0	-8.9	4.0	(1.1, 16.7)
Employment (%)					
Age < 25 currently employed vs. Age <25 work in previous year	32.9	31.5	1.3	4.3	(-7.1, 9.7)
Age <25 currently employed vs. Age <25 no work in previous year	32.9	20.2	12.7	4.7	(3.5, 21.8)
Age <25 currently employed vs. Age 25-34 currently employed	32.9	41.0	-8.2	4.1	(-16.2, -0.1)
Age <25 currently employed vs. Age 25-34 work in previous year	32.9	31.5	1.4	4.7	(-7.9, 10.7)
Age <25 currently employed vs. Age 25-34 no work in previous year	32.9	23.6	9.3	6.4	(-3.3, 21.8)
Age <25 currently employed vs. Age 35+ currently employed	32.9	35.5	-2.7	5.3	(-13.0, 7.6)
Age <25 currently employed vs. Age 35+ work in previous year	32.9	33.0	-0.2	5.7	(-11.3, 10.9)
Age <25 currently employed vs. Age 35+ no work in previous year	32.9	23.1	9.7	6.7	(-3.5, 23.0)
Duration (%)					
Greater than one semester vs. One semester or less	39.9	28.0	11.9	8.6	(-28.7, 5.0)
Previous industry (%)					
Manufacturing vs. Natural resources and mining	40.3	29.1	-11.1	8.4	(-5.4, 27.7)
Manufacturing vs. Construction	40.3	32.5	-7.7	7.4	(-6.9, 22.4)
Manufacturing vs. Trade, transportation, utilities	40.3	27.7	-12.6	5.1	(2.5, 22.7)
Manufacturing vs. Information, finance, professional, business services	40.3	24.6	-15.6	5.3	(5.2, 26.1)

Subgroup	Mean (Group 1)	Mean (Group 2)	Difference	Standard Error	95% Confidence Interval
Manufacturing vs. education, health, government	40.3	32.4	-7.9	9.8	(-11.3, 27.1)
Manufacturing vs. Leisure and hospitality	40.3	19.7	-20.6	5.3	(10.1, 31.1)
Manufacturing vs. Other services	40.3	28.8	-11.5	7.3	(2.9, 25.8)

Exhibit G-8. Expanded Results for Change in Earnings by Participant Characteristic

Subgroup	Mean (Group 1)	Mean (Group 2)	Difference	Standard Error	95% Confidence Interval
Male vs. Female ($)	2,246	2,923	-677	505	(-1667, 313)
Veteran ($)					
Citizen and veteran vs. Not citizen or veteran	3,511	2,242	1,269	858	(-412, 2950)
Public assistance ($)					
Currently receiving TRA vs. Not currently receiving TRA	-2,218	2,443	-4,661	1,674	(-7941, -380)
Currently receiving TANF vs. Not currently receiving TANF	4,232	2,334	1,898	1,183	(-421, 4217)
Currently receiving SNAP vs. Not currently receiving SNAP	1,511	2,471	-960	347	(-1640, -279)
Education Attainment ($)					
Less than high school vs. More than high school	2,328	2,328	-55	282	(-607, 497)
Duration ($)					
Greater than one semester vs. One semester or less	3,358	1,680	1,678	500	(698, 2658)
Employment ($)					
Age < 25 currently employed vs. Age <25 work in previous year	4,061	2,771	1,290	647	(22, 2559)
Age <25 currently employed vs. Age <25 no work in previous year	4,061	3,260	801	705	(-581, 2182)
Age <25 currently employed vs. Age 25-34 currently employed	4,061	2,159	1,902	447	(1026, 2778)
Age <25 currently employed vs. Age 25-34 work in previous year	4,061	952	3,109	656	(1822, 4395)
Age <25 currently employed vs. Age 25-34 no work in previous year	4,061	3,042	1,019	904	(-754, 2792)
Age <25 currently employed vs. Age 35+ currently employed	4,061	2,494	1,567	655	(283, 2851)
Age <25 currently employed vs. Age 35+ work in previous year	4,061	83	3,978	997	(2024, 5931)
Age <25 currently employed vs. Age 35+ no work in previous year	4,061	2,038	2,023	860	(337, 3708)
Previous industry (%)					
Manufacturing vs. Natural resources and mining	2,052	3920	-1867	1,478	(-4764, 1029)
Manufacturing vs. Construction	2,052	1007	1046	964	(-844, 2936)
Manufacturing vs. Trade, transportation, utilities	2,052	2194	-142	741	(-1595, 1311)
Manufacturing vs. Information, finance, professional, business services	2,052	-266	2319	1,183	(0, 4638)
Manufacturing vs. education, health, government	2,052	1143	910	970	(-991, 2810)
Manufacturing vs. Leisure and hospitality	2,052	1491	562	1,023	(-1444, 2568)
Manufacturing vs. Other services	2,052	2398	-345	1,319	(-2930, 2239)

Exhibit G-9. Expanded Results for Receipt of Public Assistance Benefits by Participant Characteristic

Subgroup	Mean (Group 1)	Mean (Group 2)	Difference	Standard Error	95% Confidence Interval
Male vs. Female	18.6	23.6	-5.0	3.7	(-2.3, 12.3)
Race/ethnicity					
White vs. Hispanic	16.2	17.6	-1.4	2.9	(-7.2, 4.3)
White vs. Black	16.2	26.7	-10.5	2.1	(-14.5, -6.5)
White vs. Other	16.2	22.5	-6.3	4.1	(-14.3, 1.7)
Veteran (%)					
Citizen and veteran vs. Not citizen or veteran	31.3	18.2	13.1	3.4	(-19.8, -6.5)
Public assistance (%)					
Currently receiving TRA vs. Not currently receiving TRA	53.3	18.7	34.6	9.9	(-54.0, -15.2)
Currently receiving TANF vs. Not currently receiving TANF	65.1	18.6	46.6	10.4	(-67.1, -26.0)
Currently receiving SNAP vs. Not currently receiving SNAP	64.0	13.8	50.3	3.7	(-57.5, -43.0)
Education Attainment (%)					
Less than high school vs. More than high school	20.2	18.6	1.6	1.8	(-5.1, 1.9)
Employment (%)					
Age < 25 currently employed vs. Age <25 work in previous year	11.0	16.2	-5.2	3.2	(-11.4, 1.1)
Age <25 currently employed vs. Age <25 no work in previous year	11.0	19.5	-8.5	3.5	(-15.5, -1.5)
Age <25 currently employed vs. Age 25-34 currently employed	11.0	15.4	-4.4	2.1	(-8.5, -0.3)
Age <25 currently employed vs. Age 25-34 work in previous year	11.0	26.4	-15.4	3.2	(-21.6, -9.2)
Age <25 currently employed vs. Age 25-34 no work in previous year	11.0	28.9	-18.0	6.2	(-30.1, -5.8)
Age <25 currently employed vs. Age 35+ currently employed	11.0	17.3	-6.3	2.6	(-11.4, -1.2)
Age <25 currently employed vs. Age 35+ work in previous year	11.0	32.2	-21.2	3.9	(-28.9, -13.5)
Age <25 currently employed vs. Age 35+ no work in previous year	11.0	40.3	-29.3	5.2	(-39.4, -19.2)
Duration (%)					
Greater than one semester vs. One semester or less	18.6	20.0	-1.4	2.8	(-4.2, 7.0)

Subgroup	Mean (Group 1)	Mean (Group 2)	Difference	Standard Error	95% Confidence Interval
Previous industry (%)					
Manufacturing vs. Natural resources and mining	32.1	25.6	6.5	9.5	(-12.1, 25.1)
Manufacturing vs. Construction	32.1	28.6	3.5	8.0	(-12.2, 19.2)
Manufacturing vs. Trade, transportation, utilities	32.1	23.2	8.9	6.7	(-4.3, 22.0)
Manufacturing vs. Information, finance, professional, business services	32.1	20.9	11.2	5.7	(0.1, 22.4)
Manufacturing vs. education, health, government	32.1	29.5	2.7	7.3	(-11.8, 17.1)
Manufacturing vs. Leisure and hospitality	32.1	28.6	3.6	8.8	(-13.9, 21.0)
Manufacturing vs. Other services	32.1	27.1	-5.0	8.3	(-11.2, 21.3)

G.3. EXPANDED RESULTS FOR CHAPTER 6

Exhibits G-10 through **G-38** contain expanded results for the analysis of participant outcomes by service receipt reported in Chapter 6.

Exhibit G-10. Expanded Results for the Analysis of Accelerated Learning Services on Program Completion in Chapter 6

Service Utilization Subgroup	Expected Completion Rate (%)	Actual Completion Rate (%)	Excess Completion Rate	Standard Error	*p*-Value
Received Transfer Credits					
Yes	42.9	43.5	0.6	5.0	
No	53.6	53.4	-0.2	3.2	
Difference	*-10.7*	*-9.9*	*0.8*	*3.7*	*.835*
Received Credit for Prior Learning					
Yes	43.2	40.1	-3.1	5.0	
No	51.7	51.9	0.2	3.4	
Difference	*-8.5*	*-11.8*	*-3.3*	*5.4*	*.542*

Exhibit G-11. Expanded Results for the Analysis of Persistence and Completion Services on Program Completion

Service Utilization Subgroup	Expected Completion Rate (%)	Actual Completion Rate (%)	Excess Completion Rate	Standard Error	*p*-Value
Received Career Counseling					
Yes	51.0	54.1	3.1	3.0	
No	51.5	49.9	-1.6	3.8	
Difference	*-0.5*	*4.2*	*4.7*	*2.5*	*.058*
Received Academic Advising					
Yes	46.1	42.6	-3.5	3.4	
No	56.2	59.4	3.2	3.7	
Difference	*-10.1*	*-16.9*	*-6.8*	*3.1*	*.027*
Received Financial Aid Advising					
Yes	45.9	43.4	-2.5	3.2	
No	53.9	55.1	1.2	3.6	
Difference	*-8.0*	*-11.6*	*-3.6*	*2.3*	*.122*
Took Any Course in Study Skills, Workplace Skills, or General Life Skills					
Yes	49.9	51.6	1.7	3.1	
No	52.6	51.2	-1.4	3.8	
Difference	*-2.7*	*0.4*	*3.1*	*2.2*	*.160*

Exhibit G-12. Expanded Results for the Analysis of Work-Based Learning on Program Completion

Service Utilization Subgroup	Expected Completion Rate (%)	Actual Completion Rate (%)	Excess Completion Rate	Standard Error	*p*-Value
Participated in Computer or Other Simulations to Practice Skills in a Virtual Setting					
Yes	47.3	48.7	1.4	4.6	
No	55.1	53.8	-1.2	3.6	
Difference	*-7.7*	*-5.1*	*2.6*	*4.8*	*.591*
Participated in Work-like Physical Environments					
Yes	52.7	56.6	3.9	3.2	
No	45.7	29.5	-16.2	3.8	
Difference	*7.0*	*27.1*	*20.1*	*3.5*	*<.001*
Offered Opportunity for Direct Occupational Experience such as a Work Study Job or Internship					
Yes	52.3	55.9	3.6	4.0	
No	50.1	45.4	-4.7	4.2	
Difference	*2.2*	*10.5*	*8.3*	*5.2*	*.109*

Exhibit G-13. Expanded Results for the Analysis of Different Service Mixtures on Program Completion

Service Mixture	Expected Completion Rate (%)	Actual Completion Rate (%)	Excess Completion Rate	Impact	Standard Error	*p*-Value
Cluster 1. Mostly classroom instruction with few other supports	53.5	44.7	-8.9	-12.1	5.3	.022
Cluster 2. Work-based learning with persistence and completion services	44.6	40.2	-4.5	-6.2	2.8	.026
Cluster 3. Work-based learning with few other supports	51.5	52.2	0.8	1.0	3.1	.733
Cluster 4. Work-based learning with employment-related services	58.6	77.5	19.0	23.2	2.3	<.001

Exhibit G-14. Expanded Results for the Analysis of Accelerated Learning Services on Training-Related Employment (excluding participants still enrolled)

Service Utilization Subgroup	Expected Employment Rate (%)	Actual Employment Rate (%)	Excess Employment Rate	Standard Error	*p*-Value
Transfer credits					
Yes	38.2	44.8	6.6	5.2	
No	31.7	30.3	-1.5	2.6	
Difference	*6.5*	*14.5*	*8.0*	*4.0*	*.046*
Prior learning					
Yes	33.1	41.2	8.1	6.2	
No	32.9	32.6	-0.3	3.1	
Difference	*0.2*	*8.6*	*8.4*	*6.6*	*.220*

Exhibit G-15. Expanded Results for the Analysis of Persistence and Completion Services on Training-Related Employment

Service Utilization Subgroup	Expected Employment Rate (%)	Actual Employment Rate (%)	Excess Employment Rate	Standard Error	*p*-Value
Career counseling					
Yes	32.0	33.5	1.4	3.1	
No	33.4	32.6	-0.8	3.4	
Difference	*-1.4*	*0.9*	*2.2*	*2.9*	*.441*
Academic advising					
Yes	31.8	31.3	-0.5	3.3	
No	33.8	34.2	0.4	3.0	
Difference	*-2.0*	*-2.9*	*-0.9*	*2.1*	*.666*
Financial aid advising					
Yes	34.1	38.2	4.2	3.5	
No	32.4	30.7	-1.7	2.8	
Difference	*1.6*	*7.5*	*5.9*	*2.3*	*.013*

Service Utilization Subgroup	Expected Employment Rate (%)	Actual Employment Rate (%)	Excess Employment Rate	Standard Error	*p*-Value
Course in study skills, workplace skills, or general life skills					
Yes	32.4	34.0	1.6	3.3	
No	33.3	32.1	-1.3	3.2	
Difference	*-1.0*	*1.9*	*2.9*	*2.4*	*.234*

Exhibit G-16. Expanded Results for the Analysis of Work-Based Learning on Training-Related Employment

Service Utilization Subgroup	Expected Employment Rate (%)	Actual Employment Rate (%)	Excess Employment Rate	Standard Error	*p*-Value
Participated in computer or other simulations to practice skills in a virtual setting					
Yes	34.7	39.7	5.0	4.0	
No	31.4	27.2	-4.2	1.9	
Difference	*3.3*	*12.5*	*9.2*	*3.1*	*.003*
Participated in work-like physical environments					
Yes	33.4	36.2	2.8	3.1	
No	30.8	18.3	-12.5	2.5	
Difference	*2.6*	*17.9*	*15.3*	*3.4*	*<.001*
Offered opportunity for direct occupational experience such as a work study job or internship					
Yes	34.6	41.0	6.4	3.8	
No	30.8	22.5	-8.3	2.1	
Difference	*3.8*	*18.5*	*14.7*	*4.1*	*<.001*

Exhibit G-17. Expanded Results for the Analysis of Employment-Related Services on Training-Related Employment

Service Utilization Subgroup	Expected Employment Rate (%)	Actual Employment Rate (%)	Excess Employment Rate	Standard Error	*p*-Value
Received job search or placement assistance					
Yes	33.3	43.8	10.4	3.7	
No	32.6	25.5	-7.2	2.3	
Difference	0.7	18.3	17.6	3.4	<.001
Received interviewing practice services					
Yes	33.8	46.2	12.4	4.2	
No	32.6	27.9	-4.7	2.4	
Difference	1.2	18.3	17.1	3.6	<.001

Exhibit G-18. Expanded Results for the Analysis of Different Service Mixtures on Training-Related Employment

Service Mixture	Expected Employment Rate (%)	Actual Employment Rate (%)	Excess Employment Rate	Impact	Standard Error	*p*-Value
Cluster 1. Mostly classroom instruction with few other supports	31.5	22.1	-9.4	-13.0	3.2	<.001
Cluster 2. Work-based learning with persistence and completion services	33.0	37.1	4.1	5.5	3.2	.086
Cluster 3. Work-based learning with few other supports	34.4	33.8	-0.6	-0.8	2.7	.760
Cluster 4. Work-based learning with employment-related services	32.7	41.3	8.6	10.8	3.1	.001

Exhibit G-19. Expanded Results for the Analysis of Accelerated Learning Services on Change in Earnings (all participants)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Received transfer credits					
Yes	$2,622	$3,109	$487	$355	
No	$2,030	$1,768	$-261	$373	
Difference	*$592*	*$1,341*	*$749*	*$378*	*.051*
Received credit for prior learning or work experience					
Yes	$2,267	$3,048	$781	$695	
No	$2,235	$2,199	$-36	$332	
Difference	$32	$849	$817	$656	.213

Exhibit G-20. Expanded Results for the Analysis of Accelerated Learning Services on Change in Earnings (participants not still enrolled)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Received transfer credits					
Yes	$2,434	$3,538	$1,104	$449	
No	$1,937	$1,815	$-122	$415	
Difference	*$496*	*$1,723*	*$1,226*	*$434*	*.005*
Received credit for prior learning or work experience					
Yes	$2,054	$2,983	$930	$865	
No	$2,096	$2,334	$239	$398	
Difference	*$-42*	*$649*	*$691*	*$763*	*.365*

Exhibit G-21. Expanded Results for the Analysis of Persistence and Completion Services on Change in Earnings (all participants)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Received career counseling					
Yes	$2,360	$2,100	$-260	$467	
No	$2,170	$2,310	$140	$307	
Difference	*$191*	*$-210*	*$-400*	*$348*	*.250*
Received academic advising					
Yes	$2,499	$2,261	$-238	$349	
No	$2,003	$2,214	$212	$361	
Difference	*$496*	*$47*	*$-449*	*$256*	*.079*
Received financial aid advising					
Yes	$2,590	$2,426	$-164	$388	
No	$2,075	$2,150	$75	$379	
Difference	*$515*	*$276*	*$-239*	*$400*	*.550*
Took any course in study skills, workplace skills, or general life skills					
Yes	$2,334	$2,322	$-12	$403	
No	$2,1545	$2,164	$10	$334	
Difference	*$179*	*$158*	*$-22*	*$322*	*.947*

Exhibit G-22. Expanded Results for the Analysis of Persistence and Completion Services on Change in Earnings (participants not still enrolled)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Received career counseling					
Yes	$2,173	$2,223	$50	$523	
No	$2,051	$2,434	$383	$373	
Difference	*$122*	*$-210*	*$-333*	*$342*	*.331*
Received academic advising					
Yes	$2,318	$2,577	$259	$465	
No	$1,920	$2,189	$269	$398	
Difference	*$398*	*$388*	*$-10*	*$309*	*.974*
Received financial aid advising					
Yes	$2,333	$2,845	$512	$435	
No	$1,996	$2,159	$163	$428	
Difference	*$337*	*$686*	*$349*	*$384*	*.364*
Took any course in study skills, workplace skills, or general life skills					
Yes	$2,142	$2,437	$294	$507	
No	$2,055	$2,297	$241	$373	
Difference	*$87*	*$140*	*$53*	*$356*	*.881*

Exhibit G-23. Expanded Results for the Analysis of Work-Based Learning of Change in Earnings (all participants)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Participated in computer or other simulations to practice skills in a virtual setting					
Yes	$2,254	$2,605	$352	$286	
No	$2,221	$1,909	$-313	$391	
Difference	*$32*	*$697*	*$665*	*$321*	*.039*
Participated in work-like physical environments					
Yes	$2,245	$2,127	$-118	$350	
No	$2,199	$2,740	$541	$508	
Difference	*$45*	*$-613*	*$-659*	*$507*	*.194*
Offered opportunity for direct occupational experience such as a work study job or internship					
Yes	$2,252	$2,212	$-40	$341	
No	$2,214	$2,273	$60	$489	
Difference	*$38*	*$-61*	*$-99*	*$479*	*.835*

Exhibit G-24. Expanded Results for the Analysis of Work-Based Learning of Change in Earnings (participants not still enrolled)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Participated in computer or other simulations to practice skills in a virtual setting					
Yes	$2,068	$2,850	$782	$319	
No	$2,116	$1,951	$-165	$456	
Difference	*$-48*	*$900*	*$947*	*$346*	*.006*
Participated in work-like physical environments					
Yes	$2,100	$2,234	$134	$419	
No	$2,064	$2,971	$908	$605	
Difference	*$36*	*$-737*	*$-774*	*$582*	*.184*
Offered opportunity for direct occupational experience such as a work study job or internship					
Yes	$2,087	$2,329	$242	$405	
No	$2,104	$2,403	$299	$570	
Difference	*$-17*	*$-74*	*$-57*	*$531*	*.914*

Exhibit G-25. Expanded Results for the Analysis of Employment-related Services on Change in Earnings (all participants)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Received job search or placement assistance					
Yes	$2,242	$2,360	$118	$500	
No	$2,232	$2,154	$-79	$312	
Difference	*$9*	*$206*	*$196*	*$459*	*.669*
Received interviewing practice services					
Yes	$2,115	$2,738	$623	$581	
No	$2,279	$2,062	$-217	$272	
Difference	*$-163*	*$677*	*$840*	*$459*	*.067*

Exhibit G-26. Expanded Results for the Analysis of Employment-related Services on Change in Earnings (participants not still enrolled)

Service Utilization Subgroup	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Standard Error	*p*-Value
Received job search or placement assistance					
Yes	$2,097	$2,564	$467	$559	
No	$2,092	$2,215	$123	$381	
Difference	$5	$350	$344	$483	.476
Received interviewing practice services					
Yes	$2,039	$2,887	$848	$632	
No	$2,116	$2,152	$36	$344	
Difference	$-77	$735	$812	$475	.088

Exhibit G-27. Expanded Results for the Analysis of Service Mixtures on Change in Earnings (all participants)

Service Mixture	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Impact	Standard Error	*p*-Value
Cluster 1. Mostly classroom instruction with few other supports	$2,141	$2,199	$58	$78	$462	.865
Cluster 2. Work-based learning with persistence and completion services	$2,640	$2,488	$-152	$-215	$454	.635
Cluster 3. Work-based learning with few other supports	$1,994	$1,813	$-180	$-246	$273	.368
Cluster 4. Work-based learning with employment-related services	$2,079	$2,511	$432	$526	$461	.253

Exhibit G-28. Expanded Results for the Analysis of Different Service Mixtures on Change in Earnings (participants not still enrolled)

Service Mixture	Expected Change in Earnings ($)	Actual Change in Earnings ($)	Excess Change in Earnings ($)	Impact	Standard Error	*p*-Value
Cluster 1. Mostly classroom instruction with few other supports	$2,045	$2,154	$109	$-213	$449	.635
Cluster 2. Work-based learning with persistence and completion services	$2,363	$2,879	$516	$339	$377	.369
Cluster 3. Work-based learning with few other supports	$1,920	$1,834	$-85	$-480	$321	.136
Cluster 4. Work-based learning with employment-related services	$2,046	$2,664	$618	$442	$456	.332

Exhibit G-29. Expanded Results for the Analysis of Accelerated Learning Services on public assistance receipt

Service Utilization Subgroup	Expected Public Assistance Receipt (%)	Actual Participation Rate (%)	Excess Public Assistance Receipt (%)	Standard Error	*p*-Value
Received transfer credits					
Yes	17.6	19.5	1.9	1.8	
No	19.9	19.4	-0.5	1.0	
Difference	*-2.3*	*0.1*	*2.4*	*2.1*	*.266*
Received credit for prior learning or work experience					
Yes	21.4	31.7	10.3	4.7	
No	19.4	18.9	-0.5	0.9	
Difference	*2.0*	*12.8*	*10.7*	*4.7*	*.038*

Exhibit G-30. Expanded Results for the Analysis of Persistence and Completion Services on Public Assistance Receipt

Service Utilization Subgroup	Expected Participation Rate (%)	Actual Public Assistance Receipt (%)	Excess Public Assistance Receipt (%)	Standard Error	*p*-Value
Received career counseling					
Yes	21.9	25.5	3.6	1.3	
Did not	18.1	16.2	-1.9	1.0	
Difference	*3.8*	*9.3*	*5.5*	*1.6*	*<.001*
Received academic advising					
Yes	19.0	22.4	3.4	1.0	
No	19.8	16.7	-3.1	1.1	
Difference	*-0.8*	*5.7*	*6.5*	*1.2*	*<.001*

Service Utilization Subgroup	Expected Participation Rate (%)	Actual Public Assistance Receipt (%)	Excess Public Assistance Receipt (%)	Standard Error	*p*-Value
Received financial aid advising					
Yes	20.6	24.4	3.8	1.3	
No	18.9	17.1	-1.8	1.1	
Difference	*1.6*	*7.3*	*5.6*	*1.8*	*.002*
Took any course in study skills, workplace skills, or general life skills					
Yes	20.1	21.4	1.3	1.2	
No	18.9	17.8	-1.1	1.1	
Difference	*1.1*	*3.5*	*2.4*	*1.6*	*.126*

Exhibit G-31. Expanded Results for the Analysis of Work-based Learning on Public Assistance Receipt

Service Utilization Subgroup	Expected Public Assistance Receipt (%)	Actual Public Assistance Receipt (%)	Excess Public Assistance Receipt (%)	Standard Error	*p*-Value
Participated in computer or other simulations to practice skills in a virtual setting					
Yes	18.8	20.7	1.9	1.4	
No	20.1	18.3	-1.8	1.2	
Difference	*-1.3*	*2.4*	*3.7*	*2.0*	*.078*
Participated in work-like physical environments					
Yes	19.4	19.5	0.1	0.9	
No	19.8	19.3	-0.5	1.8	
Difference	*-0.5*	*0.1*	*0.6*	*1.8*	*.739*
Offered opportunity for direct occupational experience such as a work study job or internship					
Yes	19.5	21.3	1.8	1.1	
No	19.4	17.0	-2.4	1.1	
Difference	*0.1*	*4.2*	*4.2*	*1.4*	*.003*

Exhibit G-32. Expanded Results for the Analysis of Employment-related Services on Public Assistance Receipt

Service Utilization Subgroup	Expected Public Assistance Receipt (%)	Actual Public Assistance Receipt (%)	Excess Public Assistance Receipt (%)	Standard Error	*p*-Value
Received job search or placement assistance					
Yes	20.5	21.4	0.9	1.2	
No	18.7	18.2	-0.6	1.2	
Difference	*1.8*	*3.2*	*1.4*	*1.6*	*.375*
Received interviewing practice services					
Yes	22.1	22.8	0.6	1.2	
No	18.5	18.3	-0.2	1.1	
Difference	*3.6*	*4.4*	*0.9*	*1.6*	*.585*

Exhibit G-33. Expanded Results for the Analysis of Different Service Mixtures on Public Assistance Receipt

Service Mixture	Expected Public Assistance Receipt (%)	Actual Public Assistance Receipt (%)	Excess Public Assistance Receipt (%)	Impact	Standard Error	*p*-Value
Cluster 1. Mostly classroom instruction with few other supports	19.5	15.6	-3.9	-5.3	1.9	.007
Cluster 2. Work-based learning with persistence and completion services	20.0	25.6	5.7	7.9	2.1	<.001
Cluster 3. Work-based learning with few other supports	17.7	16.3	-1.4	-1.9	1.6	.245
Cluster 4. Work-based learning with employment-related services	21.2	20.0	-1.2	-1.4	2.1	.489

Exhibit G-34. Expanded Results for the Analysis of Accelerated Learning Services on Poverty

Service Utilization Subgroup	Expected Poverty Rate (%)	Actual Poverty Rate (%)	Excess Poverty Rate (%)	Standard Error	*p*-Value
Received transfer credits					
Yes	30.1	28.5	-1.6	1.7	
No	35.5	36.0	0.4	1.0	
Difference	-5.4	-7.4	-2.0	1.8	.273
Received credit for prior learning or work experience					
Yes	30.9	32.1	1.2	4.0	
No	34.6	34.5	-0.1	0.9	
Difference	-3.7	-2.4	1.3	3.8	.744

Exhibit G-35. Expanded Results for the Analysis of Persistence and Completion on Poverty

Service Utilization Subgroup	Expected Poverty Rate (%)	Actual Poverty Rate (%)	Excess Poverty Rate (%)	Standard Error	*p*-Value
Received career counseling					
Yes	37.0	35.6	-1.4	1.7	
No	33.1	33.8	0.8	1.1	
Difference	3.9	1.8	-2.2	2.1	.301
Received academic advising					
Yes	34.5	33.8	-0.6	1.3	
No	34.4	35.0	0.6	1.4	
Difference	0.1	-1.2	-1.2	1.9	.525
Received financial aid advising					
Yes	36.4	36.6	0.2	1.7	
No	33.5	33.4	-0.1	1.1	
Difference	2.9	3.2	0.3	2.0	.876
Took any course in study skills, workplace skills, or general life skills					
Yes	37.0	37.3	0.3	1.4	
No	32.3	32.0	-0.3	1.2	
Difference	4.7	5.3	0.6	1.8	.746

Exhibit G-36. Expanded Results for the Analysis of Work-based Learning on Poverty

Service Utilization Subgroup	Expected Poverty Rate (%)	Actual Poverty Rate (%)	Excess Poverty Rate (%)	Standard Error	*p*-Value
Participated in computer or other simulations to practice skills in a virtual setting					
Yes	31.5	31.1	-0.4	1.6	
No	37.1	37.5	0.3	1.3	
Difference	-5.7	-6.4	-0.7	2.2	.750
Participated in work-like physical environments					
Yes	34.5	34.2	-0.3	1.1	
No	34.0	35.2	1.2	2.3	
Difference	0.6	-0.9	-1.5	2.7	.585
Offered opportunity for direct occupational experience such as a work study job or internship					
Yes	34.8	34.4	-0.4	1.3	
No	34.0	34.4	0.5	1.3	
Difference	0.8	0.0	-0.9	1.9	.656

Exhibit G-37. Expanded Results for the Analysis of Employment-related Services on Poverty

Service Utilization Subgroup	Expected Poverty Rate (%)	Actual Poverty Rate (%)	Excess Poverty Rate (%)	Standard Error	*p*-Value
Received job search or placement assistance					
Yes	36.6	35.4	-1.2	1.6	
No	33.0	33.8	0.8	1.0	
Difference	3.6	1.6	-2.0	1.7	.247
Received interviewing practice services					
Yes	38.5	35.9	-2.7	2.0	
No	33.0	33.9	0.9	1.0	
Difference	5.5	1.9	-3.6	2.2	.103

Exhibit G-38. Expanded Results for the Analysis of Different Service Mixtures on Poverty

Service Mixture	Expected Poverty Rate (%)	Actual Poverty Rate (%)	Excess Poverty Rate (%)	Impact	Standard Error	*p*-Value
Cluster 1. Mostly classroom instruction with few other supports	34.5	35.6	1.1	1.5	2.4	.548
Cluster 2. Work-based learning with persistence and completion services	35.3	35.1	-0.2	-0.3	2.2	.892
Cluster 3. Work-based learning with few other supports	30.9	30.3	-0.6	-0.8	2.0	.706
Cluster 4. Work-based learning with employment-related services	38.1	37.7	-0.4	-0.5	2.1	.810

G.4. EXPANDED RESULTS FOR CHAPTER 7

Exhibits G-39 through **G-42** contain expanded results of the analysis of outcomes by program reported in Chapter 7.

Exhibit G-39. Expanded Results for the Analysis of Program Completion by Program (%)

Program	Mean	80 Percent Credible Interval	99.9 Percent Credible Interval
CDL and Forklift (Cincinnati)	93.1	(89.8, 96.0)	(82.2, 98.7)
Core Plus (Delgado)	82.8	(79.3, 86.3)	(72.7, 90.2)
Licensed Practical Nurse (Washburn)	79.5	(73.3, 85.4)	(61.6, 92.2)
Mechanical Craft (Chaffey)	79.2	(69.2, 88.3)	(49.7, 95.6)
Emergency Medical Technician (Washburn)	74.5	(68.2, 80.5)	(58.1, 87.8)
Welding Technology (Washburn)	73.9	(63.5, 83.5)	(45.6, 92.4)
Advanced Manufacturing and Engineering (Chaffey)	67.7	(62.2, 73.1)	(53.6, 80.4)
Advanced Manufacturing (Manchester)	67.6	(63.8, 71.3)	(57.5, 76.6)
Welding Technology (Manchester)	66.1	(53.9, 78.0)	(33.3, 91.4)
Industrial Automation (Chaffey)	65.3	(54.9, 75.2)	(39.2, 87.5)
Industrial Maintenance (Chaffey)	61.2	(56.0, 66.2)	(47.7, 73.4)
TECH 101 (Delgado)	60.1	(55.6, 64.6)	(48.1, 71.3)
TRAMCON Advanced (Miami Dade)	56.6	(39.6, 73.1)	(17.7, 88.9)
TRAMCON Basic (Miami Dade)	54.1	(38.4, 69.8)	(17.0, 87.1)
Pre-engineering (Chaffey)	52.1	(37.2, 67.0)	(17.2, 86.4)
TRAMCON Foundation (Miami Dade)	51.1	(46.6, 55.6)	(40.0, 62.4)
Welding (South Central)	47.9	(41.0, 55.0)	(31.2, 65.3)
Advanced Welding Bootcamp and Program (Bossier)	42.7	(31.8, 53.8)	(18.7, 70.6)
Fast Track to Manufacturing (Bossier)	42.5	(29.1, 56.1)	(14.3, 74.7)
Certified Production Technician (South Central)	32.8	(25.5, 40.2)	(15.4, 52.6)
Right Skills Now (South Central)	27.4	(13.1, 43.5)	(2.9, 70.9)
HVAC (Chaffey)	27.3	(20.2, 34.7)	(10.7, 47.3)
Gateway Courses to IT Programs (Ivy Tech)	19.2	(13.0, 25.8)	(6.1, 37.6)
Machining (South Central)	16.6	(8.7, 25.6)	(2.3, 43.0)
Informatics (Ivy Tech)	13.7	(6.7, 21.9)	(1.7, 40.0)
Welding (Chaffey)	12.0	(7.0, 17.5)	(2.6, 30.1)
Mechatronics (South Central)	10.7	(4.9, 17.5)	(1.3, 33.0)
Network Infrastructure (Ivy Tech)	9.8	(4.6, 15.9)	(1.3, 29.5)
Software Development (Ivy Tech)	8.6	(4.7, 12.9)	(1.6, 22.5)
Information Technology Support (Ivy Tech)	4.2	(1.7, 7.2)	(0.3, 15.8)
Cyber Security (Ivy Tech)	4.1	(1.8, 6.9)	(0.4, 14.3)
Database Management (Ivy Tech)	3.7	(0.6, 8.1)	(0, 29.3)
Computer Science (Ivy Tech)	3.1	(0.7, 6.5)	(0.1, 18.3)
Server Administration (Ivy Tech)	2.5	(0.5, 5.3)	(0, 16.3)

Exhibit G-40. Expanded Results for the Analysis of Finding Training-related Employment by Program (%) (Subset to participants not still enrolled at survey follow-up)

Program	Mean	80 Percent Credible Interval	99.9 Percent Credible Interval
Licensed Practical Nurse (Washburn)	83.8	(78.1, 89.1)	(66.4, 94.9)
Welding Technology (Washburn)	56.7	(45.5, 68.0)	(27.8, 81.2)
Advanced Manufacturing (Manchester)	56.0	(52.1, 60.0)	(45.9, 66.8)
Mechanical Craft (Chaffey)	54.4	(42.6, 66.4)	(26.1, 81.2)
Machining (South Central)	52.0	(35.4, 68.7)	(15.4, 89.1)
Pre-engineering (Chaffey)	45.7	(31.3, 60.5)	(14.2, 80.1)
Industrial Automation (Chaffey)	44.9	(34.6, 55.5)	(21.2, 72.0)
Advanced Manufacturing and Engineering (Chaffey)	41.3	(35.5, 47.2)	(26.9, 55.9)
Certified Production Technician (South Central)	39.8	(31.5, 48.4)	(20.7, 63.6)
Advanced Welding Bootcamp and Program (Bossier)	37.5	(27.3, 48.1)	(14.6, 65.2)
Welding (South Central)	37.2	(30.0, 44.7)	(19.2, 56.0)
Welding Technology (Manchester)	35.2	(23.2, 47.7)	(9.8, 67.7)
Industrial Maintenance (Chaffey)	33.3	(28.4, 38.4)	(21.2, 45.8)
Fast Track to Manufacturing (Bossier)	32.2	(20.4, 44.7)	(8.5, 64.0)
TRAMCON Basic (Miami Dade)	28.2	(14.7, 42.6)	(3.7, 68.3)
Right Skills Now (South Central)	27.6	(12.1, 45.4)	(1.8, 78.1)
CDL and Forklift (Cincinnati)	27.5	(21.7, 33.4)	(14.2, 43.3)
Mechatronics (South Central)	27.5	(13.7, 43.1)	(3.8, 69.1)
TRAMCON Foundation (Miami Dade)	25.7	(21.8, 29.7)	(16.5, 36.2)
Emergency Medical Technician (Washburn)	24.2	(18.5, 30.2)	(11.6, 40.4)
HVAC (Chaffey)	23.2	(15.0, 32.0)	(6.9, 47.2)
TECH 101 (Delgado)	22.9	(18.9, 27.1)	(13.8, 33.4)
Welding (Chaffey)	20.2	(12.8, 28.2)	(5.7, 43.6)
Gateway Courses to IT Programs (Ivy Tech)	19.1	(12.6, 26.0)	(6.1, 38.6)
TRAMCON Advanced (Miami Dade)	17.6	(7.2, 29.8)	(1.3, 57.4)
Core Plus (Delgado)	17.5	(14.0, 21.0)	(9.7, 28.2)
Network Infrastructure (Ivy Tech)	12.5	(5.8, 20.4)	(1.4, 37.4)
Server Administration (Ivy Tech)	12.3	(4.2, 22.4)	(0.5, 48.8)
Cyber Security (Ivy Tech)	12.2	(6.3, 18.9)	(2.0, 34.4)
Informatics (Ivy Tech)	7.3	(2.1, 14.1)	(0.2, 34.9)
Software Development (Ivy Tech)	7.3	(3.4, 11.8)	(0.9, 23.3)
Database Management (Ivy Tech)	7.2	(1.2, 15.7)	(0.1, 59.3)
Information Technology Support (Ivy Tech)	6.7	(2.8, 11.2)	(0.4, 24.0)
Computer Science (Ivy Tech)	5.5	(1.3, 11.1)	(0.1, 29.2)

Exhibit G-41. Expanded Results for the Analysis of Change in Earnings by Program ($) (Subset to participants not still enrolled at survey follow-up)

Program	Mean	80 Percent Credible Interval	99.9 Percent Credible Interval
Server Administration (Ivy Tech)	5066	(3640, 6694)	(1775, 9880)
Cyber Security (Ivy Tech)	4835	(3347, 6530)	(1259, 8963)
Mechatronics (South Central - Ridgewater and SCCC)	4380	(3414, 5404)	(1765, 7549)
Computer Science (Ivy Tech)	4222	(2929, 5562)	(665, 8930)
Network Infrastructure (Ivy Tech)	3753	(2626, 5074)	(1104, 7833)
Informatics (Ivy Tech)	3697	(2657, 4728)	(920, 6576)
Machining (South Central)	3612	(2588, 4739)	(1004, 6517)
Welding Technology (Washburn)	3420	(2610, 4288)	(1523, 5745)
Licensed Practical Nurse (Washburn)	3239	(2709, 3779)	(1945, 4680)
Database Management (Ivy Tech)	3112	(1438, 4810)	(-1029, 7844)
Software Development (Ivy Tech)	3040	(2430, 3675)	(1467, 4822)
Welding (South Central)	2998	(2220, 3837)	(1109, 5209)
Welding Technology (Manchester)	2907	(2145, 3701)	(744, 5117)
Information Technology Support (Ivy Tech)	2561	(1815, 3354)	(692, 4915)
Mechanical Craft (Chaffey)	2522	(1806, 3268)	(730, 4501)
Right Skills Now (South Central)	2404	(1358, 3424)	(-766, 5325)
Advanced Manufacturing (Manchester)	2304	(1870, 2748)	(1225, 3458)
Welding (Chaffey)	2201	(1581, 2824)	(643, 3930)
Certified Production Technician (South Central)	2088	(1437, 2786)	(426, 4114)
Gateway Courses to IT Programs (Ivy Tech)	1935	(1145, 2749)	(-335, 4530)
Emergency Medical Technician (Washburn)	1835	(1363, 2296)	(643, 3027)
Advanced Manufacturing and Engineering (Chaffey)	1667	(1159, 2186)	(394, 3028)
HVAC (Chaffey)	1544	(874, 2211)	(-242, 3281)
TRAMCON Advanced (Miami Dade)	1476	(613, 2307)	(-894, 3831)
Advanced Welding Bootcamp and Program (Bossier)	1467	(808, 2129)	(-308, 3418)
Fast Track to Manufacturing (Bossier)	1327	(563, 2124)	(-711, 3541)
Industrial Automation (Chaffey)	1270	(453, 2037)	(-1152, 3432)
TRAMCON Basic (Miami Dade)	1088	(252, 1950)	(-1182, 3767)
Industrial Maintenance (Chaffey)	1074	(693, 1460)	(156, 2069)
Pre-engineering (Chaffey)	1011	(216, 1796)	(-1397, 3203)
TECH 101 (Delgado)	856	(520, 1189)	(-3, 1681)
TRAMCON Foundation (Miami Dade)	683	(361, 1000)	(-172, 1476)
CDL and Forklift (Cincinnati)	665	(261, 1077)	(-352, 1673)
Core Plus (Delgado)	422	(113, 733)	(-337, 1173)

Exhibit G-42. Expanded Results for the Analysis of Public Assistance Receipt by Program (%)

Program	Mean	80 Percent Credible Interval	99.9 Percent Credible Interval
Welding (Chaffey)	38.0	(33.8, 42.6)	(26.9, 51.9)
Core Plus (Delgado)	26.5	(23.8, 29.3)	(19.3, 35.0)
Industrial Automation (Chaffey)	25.5	(21.7, 29.3)	(13.6, 37.8)
Pre-engineering (Chaffey)	24.8	(20.8, 28.8)	(13.6, 40.6)
Cyber Security (Ivy Tech)	23.5	(19.6, 25.9)	(14.1, 34.3)
CDL and Forklift (Cincinnati)	22.6	(19.2, 25.9)	(13.1, 31.3)
HVAC (Chaffey)	21.8	(18.7, 25.2)	(13.4, 33.0)
TRAMCON Foundation (Miami Dade)	21.4	(19.0, 24.0)	(16.1, 29.2)
Right Skills Now (South Central)	21.2	(16.8, 25.8)	(9.3, 37.3)
Fast Track to Manufacturing (Bossier)	21.2	(17.1, 26.0)	(11.7, 42.4)
Computer Science (Ivy Tech)	21.1	(16.5, 25.7)	(10.1, 34.9)
Advanced Manufacturing (Manchester)	20.8	(18.6, 23.0)	(15.2, 27.5)
TECH 101 (Delgado)	20.4	(18.0, 22.8)	(14.2, 27.8)
Server Administration (Ivy Tech)	18.2	(14.1, 22.5)	(7.9, 33.1)
Network Infrastructure (Ivy Tech)	17.6	(14.3, 20.9)	(7.6, 28.2)
Industrial Maintenance (Chaffey)	17.2	(14.6, 19.7)	(10.0, 24.3)
TRAMCON Advanced (Miami Dade)	17.0	(13.7, 20.4)	(8.0, 30.5)
TRAMCON Basic (Miami Dade)	16.9	(13.7, 20.3)	(7.7, 30.8)
Welding Technology (Manchester)	16.8	(13.7, 19.9)	(8.6, 29.4)
Licensed Practical Nurse (Washburn)	16.5	(13.3, 19.9)	(9.3, 27.6)
Advanced Welding Bootcamp and Program (Bossier)	16.4	(13.5, 19.6)	(9.2, 29.4)
Software Development (Ivy Tech)	16.2	(13.5, 19.1)	(8.9, 26.2)
Database Management (Ivy Tech)	16.0	(11.4, 20.9)	(5.0, 33.2)
Information Technology Support (Ivy Tech)	15.9	(13.2, 18.5)	(8.2, 24.0)
Mechatronics (South Central)	15.8	(12.3, 19.7)	(7.9, 29.7)
Welding (South Central)	15.3	(13.0, 18.0)	(9.6, 24.3)
Certified Production Technician (South Central)	15.2	(12.7, 17.7)	(7.6, 23.6)
Machining (South Central)	14.8	(11.9, 17.9)	(7.4, 28.6)
Informatics (Ivy Tech)	14.6	(10.9, 18.2)	(4.9, 25.5)
Gateway Courses to IT Programs (Ivy Tech)	14.4	(11.7, 17.7)	(8.6, 29.1)
Welding Technology (Washburn)	12.9	(10.1, 15.6)	(5.0, 21.5)
Advanced Manufacturing and Engineering (Chaffey)	12.3	(9.8, 14.6)	(5.9, 18.6)
Mechanical Craft (Chaffey)	9.4	(6.7, 12.0)	(2.7, 18.0)
Emergency Medical Technician (Washburn)	8.9	(6.8, 10.9)	(3.4, 14.5)

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