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ADMINISTRATIVE DATA TO DESCRIBE THE STW: AN EXPLORATION OF RE-EMPLOYMENT USING THE PARTICIPANT INDIVIDUAL RECORD LAYOUT

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PROJECT BACKGROUND

The National Center for Science and Engineering Statistics (NCSES), George Washington University's Institute for Public Policy (GWIPP), and the Center for Regional Economic Competitiveness (CREC) partnered to map how administrative data can contribute to statistics on the Skilled Technical Workforce (STW) and Non-Degree Credentials (NDCs). GWIPP and CREC pilot tested a data quality assessment approach which aims to increase the confidence of researchers in utilizing administrative data to study the STW. The GWIPP-CREC team assessed 20 potential datasets, created a metadata repository, and catalogued 350 relevant variables across 15 of those datasets. Twelve administrative datasets were included in a data quality assessment and six informed recommendations for inter-agency collaboration.

This paper is the third in a series of three papers submitted to NCSES in 2023. Companion papers address "Potential Uses of Administrative Datasets to Complement and Inform the National Training, Education, and Workforce Survey" and "Opportunities to Understand the Skilled Technical Workforce through Improved Administrative Datasets."

OUR APPROACH

The Skilled Technical Workforce (STW) is critical to the nation's security, innovation systems, and research enterprise. Administrative data sources could help identify, expand, and fortify STW training and credentialing systems, augmenting insights from survey-based research. **In this paper, we examine the usefulness of administrative datasets to understanding STW training, credentialing, and employment outcomes, demonstrating the potential of one dataset to describe STW re-employment after unemployment.**

The STW, as defined by the National Science Board (NSB), consists of individuals who utilize science and engineering skills in their jobs but do not have a bachelor's degree. We did not find any administrative dataset on training or credentialing with coverage of the entire STW population nationwide nor with information on individuals' skills. The administrative datasets we examined contain information on occupation, training, credentialing, and education, which we considered using as proxies for skill. Few of these datasets provide information for individual record units, and these cover only subsets of the STW population.

We selected the Participant Individual Record Layout (PIRL) dataset to examine a specific subset of the Skilled Technical Workforce (STW)¹: those that have experienced unemployment or underemployment and participated in publicly funded re-employment programs. We explored why some people are successful in finding new jobs after Workforce Innovation and

¹ The NSB (National Science Board) report titled "The Skilled Technical Workforce: Crafting America's Science & Engineering Enterprise" (2019) defines the Skilled Technical Workforce (STW) as "individuals who utilize science and engineering skills in their jobs but do not have a bachelor's degree." See *The Skilled technical workforce: Crafting America's science & engineering enterprise* (NSB-2019-23), National Science Board, (2019), <https://nsf-gov-resources.nsf.gov/nsb/publications/2019/nsb201923.pdf>.

Opportunity Act (WIOA) program participation, with a focus on those with prior employment in occupations that rely on STEM skills, whose prior jobs did not require a bachelor's degree.

We identify occupations relevant to the STW following the National Science Board approach to operationalizing the STW definition in the September 2019 Science and Engineering Labor Force report.² The occupations are those that require science and engineering skills in their jobs but in which less than 50 percent of workers have a bachelor's degree. We generate a socio-demographic profile from the deidentified individual records of WIOA program participants for all participants, those with any prior occupation recorded, and for those with prior employment in STW occupations. This sets the stage for the next three steps of the analysis—determining whether this group gains any training or credentials through WIOA-funded program participation (see Table 2), if program participation and training affect employment (see Tables 3-4), and if the occupational field changes with re-employment (see Figures 1-3).

STW definitions can be improved. This approach to operationalizing the STW definition *includes* individuals in the STW group when their *occupations do not* require a bachelor's degree and *excludes* individuals whose *occupations do* require a bachelor's degree, regardless of whether the individuals have a degree. Inclusion or exclusion depends on the typical education required by the occupation but results in some mischaracterization of individuals: ten percent of the group with prior STW employment (jobs do not require BA) have a bachelor's degree. As discussed below, we find the Bachelor's degree has a positive and significant effect on re-employment.

Additional precision regarding individual education levels is possible using this dataset. The PIRL variable "prior education level" can be used to include or exclude individuals based on whether they have a bachelor's degree. The analysis in this paper uses the variable "prior education level" as an independent variable in our analysis, observing the effect of the degree on re-employment. Another approach would be to observe only workers without a bachelor's degree and not allow "prior education level" to vary.

Our analysis was limited by missing occupational information. Limited occupational information on prior employment cuts the number of potential observations in half and shifts the nature of the STW population that we can observe. Observations of occupational employment after program participation are more severely limited than observations before participation at program intake. Wage record enhancements that attach occupation to employment records would vastly improve the sample of STW workers we can identify.

² The National Science Board defines the skilled technical workforce (STW) and skilled technical workers by their STEM knowledge, skills, and abilities and lack of a bachelor's degree. NSB operationalizes this definition in 2019 by identifying occupations requiring STEM knowledge and skills but with less than 50 percent of employees in that occupation holding a bachelor's degree—"skilled technical workers, defined here as workers in occupations that employ significant levels of S&E expertise and technical knowledge and whose educational attainment is less than a bachelor's degree"—from the "Demographics of the Skilled Technical Workforce" chapter in the September 2019 Science and Engineering Labor Force report at <https://nces.nsf.gov/pubs/nsb20198/the-skilled-technical-workforce#demographics-of-the-skilled-technical-workforce>.

A training-based definition of the STW is possible using this dataset. While we use an occupation-based definition of the STW, the PIRL dataset could enable alternative approaches to operationalizing the NSB's definition of the STW. Given that detailed knowledge, skills, and abilities data is not available for individual person records in this dataset (or in any national dataset with individual records), we used prior occupation as a proxy for skills. However, this dataset offers another proxy for skills: training program completion. Specific skills could be assumed from participation in specific training.

FINDINGS

Out of seven datasets reviewed for the use case of examining the employment outcomes of the STW, the WIOA PIRL dataset was the only one with a public use file allowing for longitudinal analysis at the level of the individual record unit. The PIRL dataset is a rich and detailed resource for understanding employment dynamics for a population that experienced unemployment or underemployment and participated in WIOA programs, about 11 million individuals from 2017 to 2021.

It is possible to observe trends in credentialing and employment for the STW using this administrative dataset. We identified occupations which require STEM skills but with less than 50 percent of employees in that occupation holding a bachelor's degree, following the NSB's 2019 approach to operationalizing the STW definition.³ Using this definition, we find that

- 1) individuals with prior STW employment are participating in public workforce programs, including unemployed and dislocated workers and those experiencing barriers to work;
- 2) individuals with prior STW employment gain non-degree credentials through WIOA-sponsored training;
- 3) prior non-degree credential attainment and WIOA program training are positively correlated with re-employment for this group, with positive results for women;
- 4) this group of WIOA program participants tend to return to the same high-level occupational group upon re-employment, at similar rates as all WIOA program participants (e.g., production workers return to production and healthcare support practitioners return to healthcare support), with some overall movement into office and administrative occupations.

In providing this analysis, we sought to demonstrate the value and limitations of administrative data for understanding the STW. **The PIRL dataset is useful in efforts to train and credential the**

³ "Demographics of the Skilled Technical Workforce" chapter in the September 2019 Science and Engineering Labor Force report at <https://nces.nsf.gov/pubs/nsb20198/the-skilled-technical-workforce#demographics-of-the-skilled-technical-workforce>

STW. To fully realize the potential for this dataset to inform the policymaking, data quality improvements and attention to the peculiarities of administrative data collection processes will be necessary. The data quality would be improved if wage record matching to individual records could be expanded and if wage records could be enhanced with information on occupation or job title. In the short term, the Employment and Training Administration can continue to increase parity across states in executing high-quality data collection. In the long term, states can continue to pursue wage record enhancement to ensure information on job title is more systematically available via the Unemployment Insurance reporting systems.

Finally, this dataset includes only a subset of the STW population and working with the data requires differentiating the individual record units from the transaction records. Opportunities to increase the value of this dataset include matching individual record units with information on individuals' skills when information on skills becomes more readily available.

SELECTING THE PIRL DATASET TO STUDY THE SKILLED TECHNICAL WORKFORCE (STW)

We considered seven major public use administrative datasets for our analysis of skilled technical workers' employment outcomes and career transitions.

The datasets we evaluated were:

- Participant Individual Record Layout (PIRL)
- Eligible Training Provider Performance Results (ETPPR)
- Post-Secondary Employment Outcomes (PSEO)
- National Labor Exchange (NLx)
- Integrated Post-Secondary Education Data System (IPEDS)
- Certification/license rosters and finder tools (various)
- State Longitudinal Data Systems (SLDS)

We reviewed these with the objective of finding datasets that met the following criteria:

- Produced periodically with a publication cycle of no more than every two years.
- Data is available to the public through open data download or with a readily accessible memorandum of understanding or similar agreement.
- Data represents either a multi-state or statewide population.
- The data producer is likely to continue publication of the dataset.

We further narrowed our search to datasets that contained as many of the following variables as possible:

- Occupation information (OCC/SOC codes)
- Educational program information (CIP codes)
- Wage information

- Demographics (gender, age, race/ethnicity, and educational attainment)
- Industry information (NAICS codes)
- De-identified individual record units

None of the datasets we reviewed fully met the requirements to generate a national-level STW research dataset, but the PIRL dataset met most of the criteria. We determined that the PIRL dataset was best able to meet our research needs.

The PIRL dataset includes all U.S. states, with state identifiers for individual program participants. Unfortunately, there is incomplete information on individuals' workforce board region. The population coverage is limited to participants in federally funded workforce programs. PIRL and ETPPR datasets include SOC codes, essential for identifying STEM-relevant employment. PIRL also includes CIP codes, which identify education and training programs that are completed. Additionally, the PIRL includes education history, allowing for identification of skilled technical workers by lack of BA or higher degree attainment. The PIRL dataset includes de-identified individual record unit information, whereas the ETPPR dataset has only aggregated training participant demographics and wage outcomes by program. SLDS from various states fulfilled many of the criteria but were not available to the public nor through an MOU or similar agreement given time constraints. These were determined to be too geographically limited to contribute to nationally representative analyses. **Appendix A** includes more information on the six datasets that were not selected.

CHARACTERISTICS OF THE PARTICIPANT INDIVIDUAL RECORD LAYOUT (PIRL)

The Participant Individual Record Layout (PIRL) consists of administrative records imported from the Department of Labor (DOL) Employment and Training Administration's (ETA) grantee reporting systems. These reports include information from DOL programs authorized in the Workforce Innovation and Opportunity Act (WIOA) as well as other employment and training programs administered by DOL excluding data and reporting for WIOA Titles II (Adult Education and Family Literacy Programs) and IV (Vocational Rehabilitation Services). The purpose of this data is to track the progress of job seekers and measure participants' employment, earnings, educational attainment, and education/training progress through quarterly performance reports submitted by programs.

PIRL data includes several demographic variables often used in policy research including race/ethnicity, educational attainment, disability status, veteran status, a low-income flag, and other socio-demographic measures. The data also includes employment information including wages, occupations, and industries. Variables range in completeness. Table 1 provides information on each of the key socio-demographic variables.⁴

The PIRL is updated each quarter with records from individuals' transactions at the program level. This produces artifacts in the data which are regularly cleaned and verified by DOL ETA staff in collaboration with state agencies. Data quality issues have been well documented

⁴ Similar statistics are provided by the Employment and Training Administration in Performance Reports, though these regular reports are not specific to the STW. For example, see <https://www.dol.gov/sites/dolgov/files/ETA/Performance/pdfs/PY%202021%20WIOA%20National%20Performance%20Summary.pdf>

and the Department of Labor aims to improve data collection^{5,6}. DOL ETA staff provide training to improve data entry at the state and program level^{7,8}. Several scholars and practitioners have published reports on employment and earnings results from the public workforce system despite data quality challenges. See Hollenbeck et al 2005; Heinrich et al 2011; Hollenbeck & Huang 2014; Hendra & Hamilton 2015; Dunham et al 2020.

⁵ U.S. Government Accountability Office (GAO). (2022). *Workforce Innovation and Opportunity Act: Additional Steps Needed to Help States Collect Complete Enrollment Information*. Washington, DC: Government Accountability Office. Retrieved October 31, 2023 from <https://www.gao.gov/assets/gao-23-104830.pdf>

⁶ National Association of State Workforce Agencies. (2018). *A Changing Workforce Development Landscape – Insights into common successes, challenges, and lessons learned during the Workforce Data Project – The Current State of Data Technology Systems and Preparing for What Lies Ahead* <https://www.naswa.org/system/files/2021-03/wioareport6-18-18web.pdf>

⁷ U.S. Department of Labor, Employment and Training Administration. *WIOA Technical Assistance Resources and Tools*. Retrieved October 31, 2023 from <https://www.dol.gov/agencies/eta/performance/resources>

⁸ U.S. Department of Labor, Employment and Training Administration. (2021). *PIRL Reporting Online Resource - Release 3.0*. Retrieved October 31, 2023 from <https://performancereporting.workforcegps.org/resources/2019/10/01/13/32/PIRL-Reporting-Online-Resource>

DEFINING THE STUDY POPULATION

We identified the population of WIOA program participants in the 50 states plus the District of Columbia from approximately 2017 to 2020.⁹ We limited our analysis to people who received employment services (“participants”) under WIOA, the majority of whom become eligible for services after being unemployed or otherwise out of the labor force.¹⁰ We also limit our analysis to people who completed those employment services and for whom post-program outcomes are recorded (“exiters”). For this analysis:

Participants are those participating in one or more covered workforce program (i.e., WIOA Adult, Youth and Dislocated workers programs and Wagner-Peyser programs).¹¹

Exiters are the subset of participants who have completed workforce programs and for whom there is post-program outcome information.¹²

It is common for a single individual to have multiple records in PIRL. This happens when an individual's participation spans multiple years or, less often, if their follow-up interview occurs in the year after their exit (“exiters”). A repeated record or “transaction record” may also occur if the same person receives employment services on separate occasions during the study period. Because records may be redundant or superseded by future reports, we limit our analysis to one record per individual, using the most recent and complete record available. It is possible that some redundant records are retained, such as if participants registered separately for employment services in multiple states and were issued different ID numbers.

The result is a data set of 11,283,258 **participants**. Of these, 10,579,821 participants' records included data on their employment status two quarters after exit, and only 9,919,565 included information one year after exit (“exiters”). Therefore, our population of 9.9 million **exiters** is smaller than the full population of participants.

⁹ While we initially compiled five years of PIRL records, 2017 to 2021, we only report on those entering the system before January 1, 2021. The newest entrants lacked sufficient time for collecting post-exit/follow-up data. Due to lags in reporting, our dataset also includes some people who exited programs in 2016 but for whom data on post-exit outcomes was not collected until 2017.

¹⁰ Unemployed participants are those who reported themselves to be unemployed, soon to be unemployed, or out of the labor force at the time they entered the workforce system, which is most PIRL participants.

¹¹ Our analysis does not cover those who may have registered in the UI system but did not participate (registrants). Registrants may only have a limited engagement with the workforce system, such as simply searching for job openings on agency computers. By contrast, “participants” have received more intensive services and/or participated in formal programming.

¹² Technically all participants eventually become exiters. However, for this study, we define an exiter as a participant who not only completed UI programs but also provided information on their employment status for up to one year following completion. Thus, our population of exiters excludes former participants who did not provide follow-up information and with those still receiving employment services.

IDENTIFYING INDIVIDUALS WITH PRIOR STW EMPLOYMENT

The NSB defines the STW as having STEM knowledge and skills but no bachelor's degree. We identify membership in the STW according to WIOA program participants' last occupation prior to program participation, as a proxy for STEM skills. We don't narrow the study observations to only those individuals without a bachelor's degree; instead, we use highest level of educational attainment as a variable in our analysis to observe the effect of a bachelor's degree (and other education levels) on individuals' re-employment. In future analyses, individuals with a bachelor's degree can be excluded.

The occupations and occupational codes selected to identify employment in jobs requiring STEM skills are listed in **Appendix C**. These "STW occupations" include only occupations that are designated by the NSB as Sciences and Engineering, S&E-related, and middle skill (excluding "non-STEM") and excludes occupations in which more than 50 percent of the workers have a bachelor's degree.¹³ Therefore, observations will include some individuals with a bachelor's degree who work in occupations that do not require a degree. We examine the effect of the degree in the multivariate analysis.

Some WIOA program participants have occupational codes recorded prior to program participation (at "entry") and some have occupational codes recorded after program participation (after "exit"). Of the 11.3 million participants, there are 4.6 million with any recorded occupation prior to entry, and only 433,190 with an **STW occupation** prior to entry. There are 257,252 participants with any occupation recorded after exit, and only 24,857 with an **STW occupation** after exit.

From 11.3 million WIOA program participants...	Observations at "entry"	Observations after "exit" (not limited by entry)
Any occupation listed	4.6 million	257,252
STW occupation listed	433,190	24,857

Table 1 provides a demographic profile for all WIOA program participants and the four sub groups described above: with and without **any occupation** listed at entry and after exit; and **STW occupation** listed at entry and after exit.

¹³ These occupations are from Table SLBR-1 (SLBR-1, Supplemental, Employed adults in STEM and non-STEM occupations, by broad and detailed occupation: 2019) included in National Science Board 2021 report "The STEM Labor Force of Today: Scientists, Engineers, and Skilled Technical Workers." These were identified using the American Community Survey 2019 PUMS. 2019 PUMS Occupational Classification System occupational codes were cross walked to Standard Occupational Classification (SOC) codes used in the PIRL.

In future analysis, the NSB definition could be operationalized by excluding observations of individuals with a bachelor's degree using information on their highest level of education attainment (independent variable in this analysis) and with more granular information on skills (possible extension of this dataset).

WIOA program participants overall differ in important ways from the U.S. population.¹⁴ Men, Blacks, and Hispanics are overrepresented in WIOA programs, while non-Hispanic Whites and Asians are underrepresented. These results correlate with average national unemployment rates and income levels for these groups in the U.S. WIOA program participants who have information on outcomes captured after exit or “exitors” are even more representative of men, Blacks, Hispanics.

Those with prior employment in the STW, a subgroup of all WIOA program participants, are more like the U.S. population than their non-STW counterparts. STW occupations require STEM skills but not a bachelor's degree and also require work experience and some training beyond high school. Individuals with these prior jobs tend to be more White and Male. For example, in the manufacturing sector, machinery maintenance technicians and engineering technicians are more likely to be White and Male than operators, testers, and sorters. In healthcare, licensed practical nurses and registered nurses are more likely to be White than nursing aides and nursing assistants.

Would the results be different if we had defined the STW with a different occupation set, particularly one that was more inclusive of entry-level positions that might lead to training beyond high school and a position in the STW? By expanding the list of occupations in this way, we found more women, more Hispanics, more people with no high school or only high school as highest level of credential attainment, fewer college and Associate's degree holders, and slightly more prior attainment of non-degree certificates, slightly more Veterans, and more individuals with basic skills deficiency.

Would the results be different if we had excluded individuals with a bachelor's degree from the analysis? It would be interesting to learn more about this group of individuals with a bachelor's degree in occupations that do not require a bachelor's degree. Bachelor's degree holders were ~10 percent of our population with any STW occupation listed at entry and ~8 percent of our exitors with any STW occupation listed at exit. If bachelor's degree holders were entirely excluded, we anticipate that demographic trends would be similar but less pronounced, given that higher education levels correlate with the trends reported above.

In future analysis, researchers may consider excluding displaced homemakers or further investigating trends in their self-reported prior occupation upon program entry. Displaced homemakers are individuals who were working at home without pay, previously dependent on the income of a family member, and no longer supported by that income or at the same income level. A displaced homemaker could also be someone whose family income has not changed but who is seeking employment and is having trouble obtaining or upgrading employment.

¹⁴ U.S. Bureau of the Census (2001). American Community Survey, 5-Year Estimates Subject Tables, Table S2301

TABLE 1. SOCIO-DEMOGRAPHIC PROFILE FOR ALL PARTICIPANTS, WITH ANY OCCUPATION, WITH STW OCCUPATION

		All Participants ¹⁵		Occupation listed ¹⁶				STW Occupations			
				Entry		Exit		Entry		Exit	
		#	%	#	%	#	%	#	%	#	%
sex	Male	5,893,616	53.0	2,443,687	52.4	127,331	49.5	334,018	77.9	14,696	59.5
	Female	5,224,881	47.0	2,219,470	47.6	129,921	50.5	94,710	22.1	9,983	40.5
race and ethnicity	Hispanic (any race)	1,920,600	18.6	822,356	18.9	43,158	17.5	55,562	13.9	3,230	13.5
	Asian/Pacific Islander	295,588	2.9	118,370	2.7	6,424	2.6	9,499	2.4	599	2.5
	Black	2,651,427	25.7	1,196,134	27.5	84,945	34.5	94,406	23.6	8,732	36.6
	American Indian/Alaskan Native	128,766	1.2	52,594	1.2	3,602	1.5	7,023	1.8	385	1.6
	White	5,117,736	49.6	2,093,107	48.1	102,481	41.7	228,613	57.1	10,484	43.9
	Multi-racial	198,981	1.9	68,561	1.6	5,353	2.2	5,498	1.4	430	1.8
educational	did not complete high school	1,926,383	17.1	565,313	12.0	44,390	17.2	49,377	11.4	2,822	11.4
	high school or equivalent	4,806,788	42.6	1,960,791	41.7	126,292	48.9	196,773	45.4	13,160	52.9
	some college or associates	2,429,521	21.5	1,161,698	24.7	48,612	18.8	121,293	28.0	5,973	24.0
	non-degree certificate	309,072	2.7	135,728	2.9	7,934	3.1	21,400	4.9	978	3.9
	bachelor's or higher	1,805,558	16.0	883,494	18.8	31,100	12.0	44,342	10.2	1,923	7.7
other characteristics ¹⁷	disabled	556,134	5.5	213,548	4.9	17,155	6.9	21,300	5.3	980	4.1
	veteran	695,327	6.2	305,137	6.5	12,330	4.8	47,699	11.2	1,552	6.2
	homeless	225,968	2.0	66,966	1.4	9,780	3.8	7,160	1.7	856	3.4
	ex-offender	435,810	4.9	135,110	3.7	19,741	8.2	12,701	3.5	1,373	6.1
	low income	2,053,874	18.2	687,888	14.6	153,161	59.3	56,382	13.0	12,283	49.4
	English limitations	275,337	2.4	104,774	2.2	5,813	2.3	4,002	0.9	658	2.6

¹⁵ The population of "All Participants" includes everyone who participated in WIOA or Wagner-Peyser supported programs that were either unemployed, soon to be unemployed, or out of the labor force at the time of entry. As such, our analysis covers a near census of those seeking employment assistance services during the years of 2017 to 2020.

¹⁶ PIRL includes fields reporting the detailed Standard Occupation Codes (SOC) for each person's last primary occupation prior to unemployment, and after re-employment (if applicable). Unfortunately, the detailed occupation fields in PIRL are often left blank. This raises concerns of possible sample bias. Only 42 percent of participants reported their last occupation prior to entering the workforce system. Of those lacking an occupation at entry, only 379,612 reported either being out of the labor force or unemployed for more than 27 weeks – suggesting no recent prior work history. It is unclear why the occupation field was left blank for the remainder. An even smaller share (2%) of exiters reported an occupation after program completion. Some of the limited response is from people who were still unemployed after exit. Regardless, there is still a large number of exiters that were employed and chose not to report an occupation.

¹⁷ Beyond standard socio-demographic measures such as race, sex and education, PIRL includes other characteristics that are important to employment outcomes but rarely measured elsewhere. These include whether the participant had a qualifying disability, had English or basic skills deficiencies, or is a dislocated worker. Some indicators might be considered sensitive and may be under-reported due to social stigma or fear of discrimination, such as one's ex-offender status, homelessness, or qualifying as a displaced homemaker. Among the other characteristics reported in Table 1, the most common (19.2 percent) reported is low-income status at time of entry, which PIRL identifies by persons participating in other social safety net programs/public assistance and/or with an income below poverty thresholds. Dislocated worker is another common status covering 8.2 percent of PIRL registrants.

	All Participants ¹⁵		Occupation listed ¹⁶				STW Occupations			
	#	%	Entry		Exit		Entry		Exit	
			#	%	#	%	#	%	#	%
basic skills deficiency	337,515	3.0	99,257	2.1	56,657	21.9	7,247	1.7	2,295	9.2
displaced homemaker	76,636	0.7	22,908	0.5	963	0.4	2,305	0.5	97	0.4
dislocated worker	944,984	8.4	532,262	11.3	63,761	25.2	46,388	10.7	5,509	22.3

The STW demographic profile is different at entry and at exit. The “entry” and “exit” differences in Table 1 show that **the STW group observed at entry is more White, less Hispanic, and less Female than other program participants.** This is expected given what we know about the demographics of the STW nationwide. **In contrast, the STW defined by occupation recorded after program participation is more Female and more Black.** The STW group defined by occupations after exit is also more likely to come from a low-income household, be a dislocated worker, have a high school degree as their highest degree, or to have basic skills deficiencies.¹⁸ These results suggest the group with occupation recorded at exit is a unique subset of the STW. The different profiles could represent differences in program participation, program effects, different data collection processes according to program participation, and/or other program dynamics. The group observed with STW occupations at exit is a much smaller group than observed at entry – as noted above, there are about 25,000 individuals at exit vs 433,000 individuals at entry.

Some variability is to be expected given the relatively small number of exiters who reported occupation data. However, the observed patterns suggest that members of groups who typically face greater labor market barriers are engaged in programs more likely to report their post-exit occupation. In this case, observed differences may not be as indicative of participation or program effects as they are of differences in program participation and program record keeping. Perhaps those who have historically faced greater barriers in the labor market tend to be more active in WIOA programs or participate in programs with better record keeping and thus have greater success in securing employment or are more likely to participate in follow-up data collection efforts. Further investigation is necessary to understand these patterns.

¹⁸ See definitions from the PIRL codebook at Social Policy Research Associates 2023

PRIOR EDUCATION TRENDS FOR WIOA PARTICIPANTS

WIOA program participants tend to have less formal education compared to the U.S. population.¹⁹ Roughly 23 percent of the labor force has a bachelor's degree or higher (35 percent for those 25 years and older), while the share of WIOA program participants with a bachelor's is just 16 percent. Roughly 7 percent of the labor force did not complete high school, while 17 percent of WIOA program participants did not complete high school.

As show in Table 1 above, WIOA program participants tend to have completed high school with no higher education (~43 percent). Many have completed some college or an Associate's degree (~22 percent). The WIOA program participants with any occupation or STW occupation listed at entry have similar levels of high school completion (42 percent and 45 percent, respectively) and some college or Associate's degree (25 percent and 28 percent). Those who have any occupation or STW occupation listed at exit have higher levels of high school completion (49 percent and 53 percent) and lower levels of some college or Associate's degree (19 percent and 24 percent).

For those with STW occupation at entry, 4.9 percent have a non-degree certificate as their highest level of education, more than the 2.7 percent of all participants and 2.9 percent of participants with any occupation listed. This reflects our understanding of the STW as a group that relies more on non-degree credentials, such as certificates, for training and to gain employment. This sets the stage for the next three steps of the analysis—whether the STW individuals gain any credentials through WIOA program participation (see Table 2 below), if these credentials (proxy is “received training” in Table 4) affect re-employment, and what are the origin and destination occupations for those re-employed after program participation.

TRAINING AND CREDENTIALING GAINS THROUGH WIOA PROGRAMMING

The PIRL dataset is unique among large-scale federal datasets for the wealth of data it contains on participation in federally funded employment services programs. Of particular interest to this study is understanding the training and credentialing of the STW through these programs (see Table 2).

We find that only a small fraction (< 4 percent) of all participants in WIOA programs received training. Rates of participation in training are similar for those with any occupation listed at entry. Rates of participation in training are much higher for those with any occupation listed after exit. **For participants that received training, more than half gained an occupational credential,** such as “non-degree certificate”, a professional license, or a certification. More than five percent of all those that trained completed high school or gained a college degree.

For the group with an STW occupation recorded, likewise, only 3.6 percent participate in training. For those that participate in training, more than half gained an occupational credential.

¹⁹ U.S. Bureau of the Census (2001). American Community Survey, 5-Year Estimates Subject Tables, Table S2301

TABLE 2. PARTICIPATION IN TRAINING SERVICES LEADING TO A RECOGNIZED CREDENTIAL

	All Participants		Occupation listed				STW Occupations			
	#	%	Entry		Exit		Entry		Exit	
			#	%	#	%	#	%	#	%
no training	10,863,793	96.3	4,544,408	96.5	148,998	57.7	417,420	96.4	13,356	53.7
training, no recognized credential	159,315	1.4	61,381	1.3	33,076	12.8	6,093	1.4	2,987	12.0
high school degree or equivalent	16,603	0.1	1,774	0.0	4,290	1.7	123	0.0	104	0.4
college degree	22,163	0.2	8,466	0.2	6,224	2.4	1,008	0.2	939	3.8
occupational credential	221,360	2.0	91,004	1.9	65,746	25.4	8,545	2.0	7,471	30.1

The rate of training goes up significantly where occupation is listed after exit, suggesting a strong relationship between the recording of exit occupation and participation in programming. For the group that participated in training with any occupation recorded after exit, 60 percent gained an occupational credential (25.4 percent of all exiters with any occupation listed, as shown in Table 2). For the group with STW occupation recorded after exit (only ~24,000 observations), for those that participated in training, 65 percent gained an occupational credential (30.1 percent of all exiters with STW occupation listed, as shown in Table 2).

In the next section, we examine employment outcomes for those who received training while participants in the public workforce system. We are especially interested if those services resulted in a recognized professional or educational credential, like a certificate, professional license, or professional certification. However, for this initial analysis, we were only able to use one measure for “training” as a proxy – see “received training” in Table 4.

EMPLOYMENT AFTER PARTICIPATION IN WIOA PROGRAMMING

Among WIOA program participants with known employment outcomes (i.e., exiters), 60.4 percent found a job within the first quarter of exiting (Table 3). This includes those entering military service or registered apprenticeships. The share of workers employed after program participation remains steady across the four quarters after exit, suggesting that those who find a job tend to stay employed. **At the aggregate level, we see little difference in employment outcomes for those with any prior occupation recorded and for those with a prior STW occupation recorded.**

TABLE 3: SHARE OF WORKERS EMPLOYED AFTER PROGRAM PARTICIPATION

Quarter (after exit)	All Exiters	Known Prior Occupation	Skilled Technical Workforce
1	60.4	61.0	61.4
2	63.2	64.2	64.2
3	63.4	64.9	64.5
4	62.8	64.4	63.8



FACTORS INFLUENCING TRANSITION INTO EMPLOYMENT FOR INDIVIDUALS WITH PRIOR STW EMPLOYMENT

We next examine the factors associated with the successful transition from unemployment to employment within a year of exit from the public workforce system for individuals with prior STW employment. (See Appendix B for multivariate analysis methods and results for all program exiters.)

We use both descriptive and inferential statistical techniques to explore the influence of personal factors on the likelihood that someone transitions into employment within a year of exiting workforce programs. First, we performed a simple chi-squared significance test of whether employment rates differ according to personal attributes, including age, gender, race, education, and other characteristics.²⁰ For all participants, most paired differences are statistically significant, which is to be expected with millions of observations to work with. What's more important is the magnitude of these differences.

For all participants, education stands out among the most important factors leading to improved employment prospects. Compared to someone who did not graduate from high school, having a bachelor's degree increases the prospects of employment by 32 percent. Getting an associate's degree or just attending some college increases employment rates by 29 percent. If an individual never went to college, getting a post-secondary professional certificate has roughly the same impact on employment as having a high school diploma, both increasing chances of employment by roughly 25 percent.

Regardless of someone's formal education, those that receive training through WIOA programs are more likely to find employment. Those that faced more difficulty finding employment included those with disabilities, the homeless, displaced homemakers, veterans, and Native Americans.²¹

The multivariate analysis results for individuals with a prior STW occupation, or STW occupation "at entry"²² are similar, though magnitudes differ. Higher levels of education are positively correlated with re-employment for individuals with a prior STW occupation. Participation in

²⁰ Most personal attributes are binary (yes/no), in which case we test the difference of one group versus the other. For age, we divide the population into two group (high and low) by the median and proceed similarly. For attributes with multiple categories, such as race and educational attainment, we test each characteristic separately against a common reference outcome. For race we use White as the comparison group. For educational attainment the reference group is made up of those who did not complete high school. Because of the relatively small numbers, we combined all those who participated in UI sponsored training programs into a single group, regardless of whether they attained a credential as a consequence of their training or not.

²¹ Persons with disabilities seem to face the greatest difficulty finding employment. They are 27 percent less likely to be employed a year after exiting compared to those without a disability. The homeless, displaced homemakers, and veterans are also less likely to find employment within a year of exit. Aside from Native Americans, who face steep barriers to re-employment, race has only a small influence on re-employment prospects, with Blacks and Hispanics having slightly better re-employment rates than Whites. Re-employment rates for women and men are just about equal.

²² Only those with STW occupation prior to participation in WIOA programs were included in the multivariate analysis, regardless of their employment after program participation. Future research should explore dynamics for the group that had STW occupations only after (smaller number of observations) and for the group that retained or regained STW employment (even smaller group).

training is positively correlated with re-employment for individuals with a prior STW occupation. Among workers with prior STW occupations, workers with disabilities, the homeless, and Native Americans still face the largest barriers to re-employment. However, dislocated and Black workers with prior STW occupations are less likely to find a job than all participants.

Going through a training program (“received training”) increases re-employment chances for individuals with prior STW occupations. Veterans and females with prior STW occupations have slightly better prospects of finding employment. For those with prior STW occupations, being a displaced homemaker (a very small group) is no longer a significant barrier to re-employment. Higher levels of formal education and credential attainment, although still overwhelmingly beneficial to finding employment, are relatively less important to the re-employment of those coming from STW occupations.

TABLE 4. LOGISTIC REGRESSION RESULTS, STW AT ENTRY

	Estimate	Odds Ratio	Standard Error	z value	Pr > z	Signif.
Intercept	-0.272	0.762	0.038	-7.104	0.000	***
2017	-0.692	0.501	0.014	-47.893	0.000	***
2018	-0.108	0.898	0.014	-7.857	0.000	***
2019	-0.115	0.891	0.015	-7.792	0.000	***
2020	-0.085	0.919	0.015	-5.785	0.000	***
Age	0.054	1.055	0.002	31.928	0.000	***
age (squared)	-0.001	0.999	0.000	-44.103	0.000	***
Female	0.082	1.085	0.009	9.532	0.000	***
Hispanic (any race)	0.012	1.012	0.010	1.133	0.257	
Asian/Pacific Islander	-0.041	0.960	0.023	-1.812	0.070	.
Black	-0.057	0.945	0.009	-6.668	0.000	***
American Indian/Alaskan Native	-0.351	0.704	0.025	-13.775	0.000	***
more than one race	-0.207	0.813	0.029	-7.063	0.000	***
disability	-0.607	0.545	0.016	-38.540	0.000	***
veteran	-0.040	0.961	0.012	-3.448	0.000	***
homeless	-0.390	0.677	0.029	-13.634	0.000	***
low income	-0.223	0.800	0.011	-20.667	0.000	***
limited english	-0.124	0.883	0.036	-3.464	0.000	***
lack basic skills	0.107	1.113	0.028	3.875	0.000	***
displaced homemaker	-0.050	0.951	0.049	-1.021	0.307	
dislocated worker	-0.138	0.871	0.012	-11.647	0.000	***
high school diploma	0.220	1.246	0.011	19.205	0.000	***
some college/associates	0.347	1.415	0.012	28.118	0.000	***
non-degree certificate	0.361	1.435	0.019	19.278	0.000	***
bachelors or higher	0.413	1.511	0.015	27.125	0.000	***
received training	0.605	1.831	0.021	29.485	0.000	***

Signif. codes: 0 <= '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < '.' < 0.1 < '' < 1

Akaike Information Criterion: 483881.2089

Null deviance: 501726.7998 on 367538 df ; Residual deviance: 483829.2089 on 367513 df

MOVEMENT BETWEEN OCCUPATIONS

In the following analysis, we examine the occupational destinations of individuals with prior STW occupations. This includes all individuals whose prior occupations required STEM skills but did not require a bachelor’s degree. Ten percent of this group are individuals with a bachelor’s degree not required for their job.

Figure 2 compares the occupation groups of individuals prior to unemployment (origin) to their occupational groups two quarters after exit (destination). The **origin** occupations, recorded in PIRL at the six-digit detailed level, are aggregated to the major 2-digit level and shown along the **x-axis**. For example, all production workers are grouped together as “production workers” for major occupational group “51”. Not all 22 major occupational fields are shown because there are no STW occupations that fall into major 2-digit SOC codes 21, 23, 25, 31, 37, 39, 41, 43, 45. All major occupational groups are listed as potential **destination** occupation fields on the **y-axis**.

Occupational Groups with Two-Digit SOC Codes

- Transportation and Material Moving (53)
- Production (51)
- Installation, Maintenance, and Repair (49)
- Construction and Extraction (47)
- Farming, Fishing, and Forestry (45)
- Office and Administrative Support (43)
- Sales and Related (41)
- Personal Care and Service (39)
- Building and Grounds Cleaning and Maintenance (37)
- Food Preparation and Serving Related (35)
- Protective Service (33)
- Healthcare Support (31)
- Healthcare Practitioners and Technical (29)
- Arts, Design, Entertainment, Sports, and Media (27)
- Educational Instruction and Library (25)
- Legal (23)
- Community and Social Service (21)
- Life, Physical, and Social Science (19)
- Architecture and Engineering (17)
- Computer and Mathematical (15)
- Business and Financial Operations (13)
- Management (11)

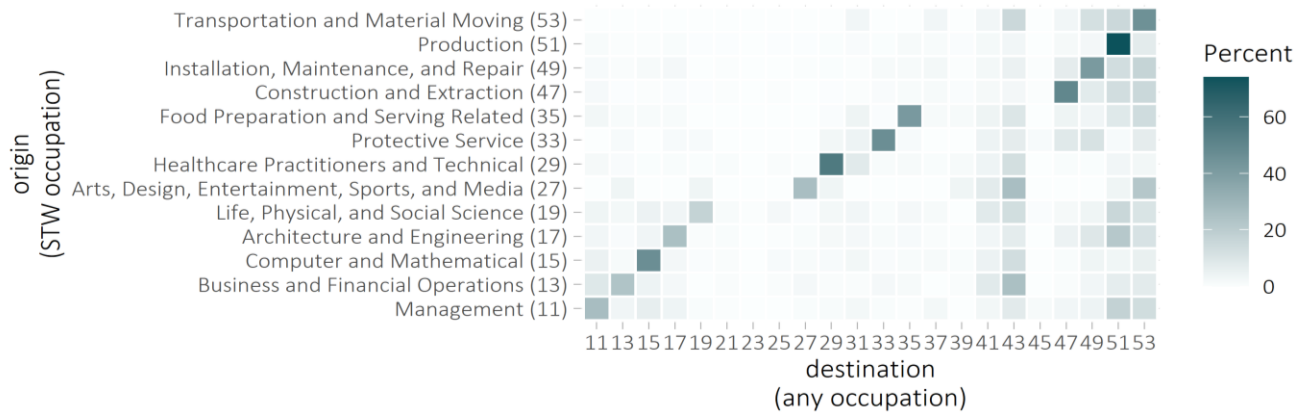
Among those exiting the public workforce system and hired within a year of program completion, most tend to find work in a closely related occupational field. This is clear from Figure 2, where percentages along the principal diagonal (representing re-employment in same occupation group) are always highest. (These results are similar to the results for all participants regardless of origin occupation—see Appendix C results for all origin occupations.)

Of the thirteen major occupation groups listed, **Production workers** were most likely to find re-employment in the same occupation group. This is followed closely by **Healthcare Practitioners and Technical workers**.

Individuals with prior employment in Life, Physical and Social Science-based occupations are most likely to “defect” to other occupation groups.²³ A few occupation groups are more common destinations for individuals entering new fields: the Office and Administrative Support occupation group (2-digit SOC code 43) is one such “sponge.” It attracts workers from many other areas, most notably Arts Design, Business Finance Operations. Other common destination occupation groups include Transportation and Material Moving, Production, and Sales and Related (2-digit SOC code 41).

²³ For all participants, other low-retention occupation groups include Legal; Arts, Design, Entertainment, Sports, and Media; and Management.

FIGURE 1. TRANSITION FROM ONE OCCUPATION GROUP TO ANOTHER, ORIGIN STW OCCUPATIONS (AT ENTRY) AND DESTINATION OCCUPATIONS (AFTER EXIT)²⁴



²⁴ The numbers in the parentheses are 2-digit SOC codes.

CONCLUSION AND DISCUSSION

The PIRL dataset offers a rare opportunity to understand participants moving through the public workforce system in the U.S. Its expansive coverage of the system and the high level of detail for millions of participants make it an important resource for understanding how individuals re-enter employment from periods of unemployment. Even with the high number of variables we considered, we are still just scratching the surface. Among the hundreds of variables we did not examine are the many covering the types of services received.

The most challenging issue for analysis of STW training, credentialing, and employment outcomes is the incomplete information on occupations before and after services, and particularly afterward. It is common for administrative datasets to be incomplete as they are not created for statistical purposes but rather to aid in program delivery. Especially after program delivery, it is difficult to collect and validate detailed information from former WIOA program participants. Of the 11,283,258 participants in our full database, 9,919,565 included information on their employment status one year after exit, but occupational details were sparse. Only four percent of participants reported their occupation prior to entering the workforce system. Less than one percent of exiters reported an occupation following participation. This issue puts serious limitations on understanding the STW in this system and the effect of credentials and training on re-employment.

A long-term solution is for job title and hours to be included in wage records from companies complying with state Unemployment Insurance reporting requirements, further populating PIRL with information on employment status and occupation from this data source.²⁵ In the near-term, there are improvements needed to reduce differences between states in data reporting practices. DOL ETA has offered various forms of technical assistance to enhance data quality with a focus on data entry. These include tools for data-related technical assistance, reporting-related technical assistance, and the Workforce Integrated Performance System (WIPS).²⁶ The data-related technical assistance tools include a resource page for WIOA credential attainment measurement. Additional online resources are provided via the WorkforceGPS²⁷ website regarding PIRL reporting.

With these limitations and ongoing efforts to improve the data, we aimed to illustrate some possible uses of PIRL to study the STW and relevant training and credentialing. Our focus was modeling the individual transitions from unemployment into employment through WIOA program participation. More exploratory than theory-testing, we developed a list of personal attributes (age, race/ethnicity, education, other characteristics) and estimated a multivariate statistical model of their independent effects.

²⁵ See <https://www.bls.gov/advisory/bloc/ui-wage-records-report-january-2022.pdf> and more information is available from the Labor Market Information Institute, for example <https://www.lmiontheweb.org/events/state-trends-and-indianas-experiences-on-enhanced-wage-records-02-2022/>

²⁶ "WIOA Technical Assistance Resources and Tools", DOL. (n.d.), <https://www.dol.gov/agencies/eta/Performance/resources>.

²⁷ "WorkforceGPS - PIRL Reporting Online Resource - Release 3.0," (n.d.), <https://performancereporting.workforcegps.org/resources/2019/10/01/13/32/PIRL-Reporting-Online-Resource>.

It was interesting to find that, while those with prior employment in the STW were more likely to be White and Male than all WIOA program participants, those who record an STW occupation after program participation are more likely to be Female and Black. This latter group is also more likely to include individuals who are identified as “low-income” with “basic skills deficiency” or “dislocated worker.” These trends are likely due to the types of programs that lead to individuals reporting any occupation at all, as similar dynamics are observed for the group reporting any occupation. Members of groups that typically face greater labor market barriers may be engaged in programs more likely to report their post-exit occupation.

In our multivariate analysis, we found that the factors that were most relevant for explaining the likelihood of re-employment were education level, race/ethnicity, disability, and barriers to employment. **Training was particularly effective for the re-employment of individuals with a prior STW occupation. Veterans and females in this group had better chances of re-employment than others.**

We also found that individuals with prior employment in STW occupations categorized as Production and Healthcare were most likely to find re-employment in the same occupation group. Individuals with prior employment in Life, Physical and Social Science-based occupations are most likely to “defect” to other occupation groups. Future studies could explore these trends for more detailed occupational fields (using four-digit detail instead of two-digit SOC codes) and, with more information from wage records, investigate whether workers are getting re-hired by their former employers or industries or whether they are finding jobs with new employers and new industries that utilize their prior experience.

With a small change in the approach, using the “prior education” variable to exclude individuals with a bachelor’s degree instead of including this as an independent variable, future research could further identify the STW within a major public-use administrative dataset and analyze career transitions for subsets of the STW. Future research could further identify under what conditions training and credentialing improve STW employment outcomes, such as for workers who are in the STW before *and* after WIOA program participation.

For those interested in improving public workforce programs, it is important to note that reform efforts, including WIOA enactment in 2014, have focused on ensuring programs provide opportunities for low-wage and dislocated workers to enter in-demand jobs and career paths that offer better wages (Hendra & Hamilton 2015; WIOA legislation), such as entering the STW or upskilling through skilled technical work. Identifying the STW in this dataset is therefore a critical test of whether the data systems are fit to capture progress toward much needed progress.

There is also an opportunity for more information on skills to eventually be linked to this dataset. More skills data could be available in the long term via efforts to create digital records of skill attainment for individuals; in the medium-term by updating reporting processes to include more specific records of skill gains for program participants; and in the near term by using proxies like job postings and training curriculum with detailed skills data, which can be associated with individuals’ jobs held and training participation to assume skillsets.



The PIRL dataset has the potential to serve as a model for making more deidentified individual unit record information available for research, such as public use versions of PSEO and SLDS that retain participant information. These types of datasets are critical to the National Science Board (NSB) mission to expand the STW and especially through training and credentialing. This requires broader public awareness of who is in the STW and what type of training and credentialing they require. NCSSES can encourage other federal agencies to provide access to more granular administrative data, such as from the PIRL dataset, to describe occupational trends for key geographies. If more administrative datasets with individual record units were linked, they could tell us about:

- Has the STW benefited from participation in public workforce programs and higher education programs over the past three years – how many increased their wages or otherwise improved their economic outlook via these programs?
- What are the most prevalent training experiences for the STW, and which result in the greatest economic gains for STW workers?

APPENDIX A: OTHER DATASETS CONSIDERED

POSTSECONDARY EMPLOYMENT OUTCOMES (PSEO)

Postsecondary Employment Outcomes (PSEO) is a project led by the US Census Bureau to combine individual level education outcomes derived from administrative data. Participation by data contributors, primarily college systems, is voluntary, making coverage within this dataset incomplete. Currently, there are contributions from 27 of the 51 states (including DC) representing between 11% (PA) and 87% (VA) of college graduates for each state (U.S. Census Bureau n.d.). Census classifies this dataset as “experimental” and there is still a concerted effort to increase the representation in the data by adding additional participants.

PSEO is designed to trace individuals from college to workforce and report on individual outcomes at the program level, including information on wages and industry of employment. The public data contains no occupational indicators, making it difficult to identify STW-relevant programs. Utilizing a CIP/SOC linkage, we could infer STW relevance from instructional programs. But public access to the underlying individual-level datasets is severely limited. PSEO Explorer, the public facing data tool for the program, draws from de-identified source files that are made public. At the time of writing, these files limit the CIP codes listed to two-digit codes rather than the 6-digit codes described in the program schema documentation (U.S. Census Bureau 2022). This limited information is insufficient for linking using the CIP/SOC crosswalk to identify STW occupations. Therefore, we find that we are unable to use public PSEO data for this study. Use of microdata under a memorandum of use agreement was explored but found to be impractical in the time available to complete this project.

ELIGIBLE TRAINING PROVIDER PERFORMANCE RESULTS (ETPPR)

Eligible Training Provider Performance Results (ETPPR) is a program search tool developed to support job seekers who are interested in reskilling/upskilling under WIOA programs. The underlying dataset includes education and employment data for nearly 75,000 training programs nationwide serving more than 4.2 million students. The dataset contains both program and occupation information as well as program-level aggregated wage information.

Information on the program participants in the ETPPR dataset is aggregated with no information on education levels to differentiate the STW from STEM occupations, such as whether or not participants tend to have a bachelor's degree. Similar information is available in the WIOA PIRL dataset selected for this study, with detail at the level of the individual participant, including their prior occupation, education level, and wage outcomes.

NATIONAL LABOR EXCHANGE (NLX)

The National Labor Exchange (NLX) Research Hub job posting database is the result of a nonprofit national partnership between state workforce agencies and employers. As of this writing, 300,000 employers had posted 2.7 million unique jobs through the NLX to state job sites. The job postings are provided as linked text with minimal metadata and potential for extracting machine-readable datasets from the text provided by NLX.

NLx is a rich source of important employment data but access to information on occupational codes and credentials is limited and salaries or salary ranges are rarely included by the participating employers.. We are aware of efforts by third parties, including NSF-supported projects, to extract and augment the information and create machine-readable data from unstructured job description text. While job postings are useful for better understanding the STW, they are not linked to information on individual applicants or hires, and cannot tell us about employment outcomes for individuals in the STW.

INTEGRATED POST-SECONDARY EDUCATION DATA SYSTEM (IPEDS)

The Integrated Post-Secondary Education Data System (IPEDS), maintained by the National Center for Education Statistics of the U.S. Department of Education, is an administrative dataset containing information on student enrollment and demographic information for students at the level of field of study for degrees or certificates. Information is reported by all higher education institutions at which students are eligible for financial assistance under Title IV of the Higher Education Act of 1965. The source of the data from institutions is student-level data, but data is aggregated at the institution level or, for program completion, at the level of fields of study and degree/certificate type. IPEDS does not contain records on labor market outcomes, neither earnings nor occupational outcome information. Therefore, we were unable to use IPEDS as a data source for this study.

CERTIFICATION AND LICENSE LISTS AND ROSTERS

Data on certifications and licenses maintained by the Employment and Training Administration provides detail on credentials linked to occupational codes but no information on participants or recipients.State-level rosters of licensed individuals, maintained by state agencies and licensing boards, contain personally identifying information on licensed individuals that could be linked to employment and earnings outcome information such as wage records or to post-secondary degree and certificate attainment records from the National Student Clearinghouse. Accessing the data and establishing such linkages would require the negotiation of data use agreements on an agency-by-agency and institution-by-institution basis. This amount of effort and associated timeline was prohibitive for this study.

STATE LONGITUDINAL DATA SYSTEMS (SLDS)

Finally, we considered analyzing data held in state longitudinal data systems (SLDSs). SLDSs are maintained by all states (except New Mexico, where one is under development), plus the District of Columbia and territories. SLDSs contain administrative data from unemployment insurance wage records and records on educational attainment from K-12 and higher education systems. Some states integrate additional data sources, such as datasets covering driver licensing, occupational licensing, and criminal records.

We did not collect SLDS data to support our analysis for several reasons. One is that these are state-level data sources not national. SLDSs typically include only information on individuals while they are studying or working in the state and not when they leave the state. It is also not clear which states currently have data on non-degree credentials in their SLDS. Certificates issued by a state's higher education system, licenses, and registered apprenticeships may be relatively simple to integrate, but industry certifications and certificates issued by organizations

other than colleges and universities are unlikely to be integrated into any state's data system at a substantial level due to the difficulty inherent in coordinating with private organizations. Moreover, data on individuals' occupations is not available in most SLDSs, making it impossible to isolate workers who are part of the STW. Privacy restrictions also make the process of applying for research use of SLDSs cumbersome.

APPENDIX B: MULTIVARIATE ANALYSIS METHODS AND RESULTS FOR ALL PROGRAM EXITERS

Model development

While useful for identifying overall patterns, the simple comparisons represented in Table 4 cannot disentangle the independent contributions of overlapping factors like education, race and gender. For this purpose, we developed a multivariate statistical model. Because our outcome is binary (employed or not employed after one year of exit) we use logistic regression (a.k.a. logit) to estimate how an individual's attributes and education influence the likelihood of transitioning into employment. A logit model is based on the equation:

$$p(Y) = \frac{e^{(\beta_0 + \beta_1 X)}}{1 + e^{(\beta_0 + \beta_1 X)}} \quad (1)$$

where the probability of moving into employment from an initial state of non-employment ($p(Y)$) is a function of a variety of independent variables (X) representing personal endowments and contextual factors. Rearranging terms and taking logs of both sides of the equation results in a linear function:

$$\log\left(\frac{p(Y)}{1-p(Y)}\right) = \beta_0 + \beta_1 X \quad (2)$$

whose unknown coefficients (β) can be estimated via maximum likelihood. While the specific values of the coefficients (β) lack any intuitive meaning, the exponents of the coefficients can be interpreted as odds ratios.

Our list of independent variables matches the personal characteristics explored in Table 4, with the addition of a squared term for the age variable that allows for a possible non-linear relationship and several year dummy variables to control for any otherwise unmeasured cyclical/temporal effects.

Results of Multivariate Analysis for All WIOA Program Exiters

Our multivariate results largely coincide with our preliminary findings (Table 4). Age has a non-linear association with the successful transition into employment. As one ages, they are more likely to find work. However, the negative sign on the age squared term suggests that employment prospects diminish over time and may eventually reach an inflection point after which getting older has a net negative impact on finding work. Hispanics and Blacks have a greater likelihood of finding employment one year after exit compared to Whites (our reference group). However, the likelihood of Native Americans finding employment within a year of exit is only 74 percent that of Whites. Women are slightly more likely to be employed a year after exit compared to men. However, displaced homemakers (who are typically female) have a sizable 25 percent disadvantage in finding employment. People with disabilities also have considerable difficulty transitioning into employment. Their chances of finding employment within a year of exit is nearly half that of non-disabled persons. These latter

two results reinforce how personal and familial challenges often complicate attempts to secure employment.

Low-income people and the homeless also have a relatively harder time finding work. Their odds of finding employment are about 74 to 82 percent that of other exiters. Contrary to expectations, those with basic and language skill deficiencies do not face diminished prospects of finding work. In fact, entrants that lack basic skills are more likely to be employed a year upon exit compared to those with basic skills proficiency. While it is doubtful that the absence of basic skills improves one's marketability, it could be that these people are more likely to benefit from job placement and/or other services offered through the UI system. The benefits of formal education clearly stand out. The more education, the more likely the person returned to work within a year of exiting the UI system. To put this in context, those with a bachelor's degree are nearly two times as likely to be employed as those without a high school diploma.

TABLE 5. LOGISTIC REGRESSION RESULTS, ALL EXITERS

	Estimate	Odds Ratio	Standard Error	z value	Pr > z	Signif.
Intercent	-0.316	0.729	0.006	-49.256	0	***
2017	-0.523	0.593	0.003	-205.125	0	***
2018	-0.136	0.873	0.002	-58.404	0	***
2019	-0.135	0.874	0.002	-55.705	0	***
2020	-0.303	0.739	0.002	-126.826	0	***
Age	0.039	1.040	0.000	131.459	0	***
age (squared)	-0.001	0.999	0.000	-191.646	0	***
Female	0.006	1.006	0.001	4.327	0	***
Hispanic (any race)	0.096	1.101	0.002	50.083	0	***
Asian/Pacific Islander	-0.047	0.954	0.004	-11.394	0	***
Black	0.041	1.042	0.002	24.338	0	***
American Indian/Alaskan Native	-0.312	0.732	0.006	-51.561	0	***
more than one race	-0.069	0.933	0.005	-13.816	0	***
Disability	-0.532	0.587	0.003	-173.108	0	***
Veteran	-0.073	0.930	0.003	-24.641	0	***
Homeless	-0.305	0.737	0.005	-60.571	0	***
low income	-0.200	0.819	0.002	-103.786	0	***
limited English	0.101	1.106	0.004	22.653	0	***
lack basic skills	0.144	1.155	0.004	33.955	0	***
displaced homemaker	-0.288	0.750	0.008	-34.420	0	***
dislocated worker	0.018	1.018	0.003	6.849	0	***
high school diploma	0.456	1.578	0.002	229.778	0	***
some college/associates	0.573	1.774	0.002	251.494	0	***
non-degree certificate	0.518	1.679	0.004	117.084	0	***
bachelors or higher	0.679	1.972	0.003	271.625	0	***
received training	0.461	1.586	0.004	119.665	0	***

Signif. codes: 0 <= '***' < 0.001 < '**' < 0.01 < '*' < 0.05 < '.' < 0.1 < '' < 1

Akaike Information Criterion: 12202464.0728

Null deviance: 12598644.3444 on 9181990 df ; Residual deviance: 12202412.0728 on 9181965 df

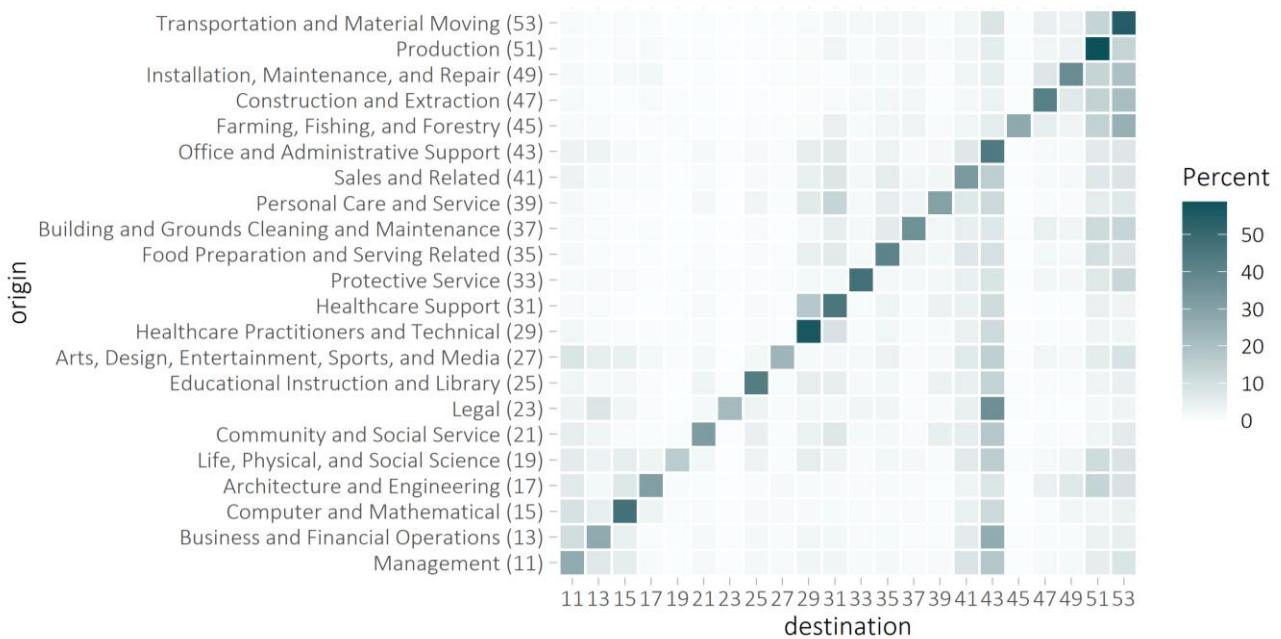
APPENDIX C: OCCUPATION GROUP TRANSITIONS FOR ALL ORIGIN OCCUPATIONS

Production workers were most likely to find re-employment in the same occupation group (58%). This is followed closely by **Healthcare** Practitioners and Technical workers (57%), Transportation and Material Moving (55%), Protective Services (47%), Computer and Mathematical Occupations (47%), and Healthcare Support occupations (46%).

Workers with prior employment in Life, Physical and Social Science-based occupations are most likely to “defect” to other occupation groups; only 16% return to jobs within the same occupational group after WIOA program participation. Other low-retention occupation groups include Legal; Arts, Design, Entertainment, Sports, and Media; and Management.

A few occupation groups are more common destinations for individuals entering new fields: the Office and Administrative Support occupation group (2-digit SOC code 43) attracts workers from many other areas, most notably Legal, Business Finance Operations, and Management.

FIGURE 2. TRANSITION FROM ONE OCCUPATION GROUP TO ANOTHER, ALL OCCUPATIONS²⁸



²⁸ The numbers in the parentheses are 2-digit SOC codes.

APPENDIX D: STW OCCUPATION LIST

Census Code	SOC Code	Occupation Title
140	11-3051	Industrial production managers
205	11-9013	Farmers, ranchers, and other agricultural managers
700	13-1081	Logisticians
930	13-2081	Tax examiners and collectors, and revenue agents
1050	15-1151	Computer User Support Specialists
1050	15-1152	Computer Network Support Specialists
1541	17-3011	Architectural and Civil Drafters
1545	17-3012	Electrical and Electronics Drafters
1545	17-3013	Mechanical Drafters
1545	17-3019	Drafters, All Other
1551	17-3023	Electrical and electronic engineering technologists and technicians
1555	17-3021	Aerospace Engineering and Operations Technicians
1555	17-3022	Civil Engineering Technicians
1555	17-3024	Electro-Mechanical Technicians
1555	17-3025	Environmental Engineering Technicians
1555	17-3026	Industrial Engineering Technicians
1555	17-3027	Mechanical Engineering Technicians
1555	17-3029	Engineering Technicians, Except Drafters, All Other
1560	17-3031	Surveying and mapping technicians
1900	19-4011	Agricultural and food science technicians
1910	19-4021	Biological technicians
1920	19-4031	Chemical technicians
1935	19-4051	Environmental science and geoscience technicians, and nuclear technicians
1970	19-4091	Environmental Science and Protection Technicians, Including Health
1970	19-4092	Forensic Science Technicians
1970	19-4093	Forest and Conservation Technicians
1970	19-4099	Life, Physical, and Social Science Technicians, All Other
1980	29-9011	Occupational Health and Safety Specialists
1980	29-9012	Occupational Health and Safety Technicians
2910	27-4021	Photographers
2905	27-4099	Other media and communication equipment workers
3220	29-1126	Respiratory therapists
3300	29-2011	Medical and Clinical Laboratory Technologists
3300	29-2012	Medical and Clinical Laboratory Technicians
3310	29-2021	Dental hygienists
3321	29-2031	Cardiovascular Technologists and Technicians
3322	29-2032	Diagnostic Medical Sonographers
3323	29-2033	Nuclear Medicine Technologists
3324	29-2034	Radiologic Technologists
3324	29-2035	Magnetic Resonance Imaging Technologists
3401 & 3402	29-2041	Emergency Medical Technicians and Paramedics

Census Code	SOC Code	Occupation Title
3421	29-2052	Pharmacy Technicians
3422	29-2053	Psychiatric Technicians
3423	29-2055	Surgical Technologists
3424	29-2056	Veterinary Technologists and Technicians
3430	29-2051	Dietetic Technicians
	29-2054	Respiratory Therapy Technicians
	29-2057	Ophthalmic Medical Technicians
3500	29-2061	Licensed practical and licensed vocational nurses
3515	29-2071	Medical records specialists
3520	29-2081	Opticians, dispensing
3545	29-9091	Athletic Trainers
3545	29-9092	Genetic Counselors
3545	29-9099	Healthcare Practitioners and Technical Workers, All Other
3740	33-2011	Firefighters
9410	53-6051	Transportation inspectors
4000	35-1011	Chefs and head cooks
6200	47-1011	First-line supervisors of construction trades and extraction workers
6210	47-2011	Boilermakers
6220	47-2021	Brickmasons and Blockmasons
6220	47-2022	Stonemasons
6230	47-2031	Carpenters
6330	47-2081	Drywall and Ceiling Tile Installers
6330	47-2082	Tapers
6355	47-2111	Electricians
6360	47-2121	Glaziers
6441	47-2151	Pipelayers
6442	47-2152	Plumbers, Pipefitters, and Steamfitters
6515	47-2181	Roofers
6530	47-2221	Structural iron and steel workers
6540	47-2231	Solar photovoltaic installers
6660	47-4011	Construction and building inspectors
6700	47-4021	Elevator and escalator installers and repairers
6800	47-5011	Derrick Operators, Oil and Gas
6800	47-5012	Rotary Drill Operators, Oil and Gas
6800	47-5013	Service Unit Operators, Oil, Gas, and Mining
6825	47-5021	Earth Drillers, Except Oil and Gas
7000	49-1011	First-line supervisors of mechanics, installers, and repairers
7010	49-2011	Computer, automated teller, and office machine repairers
7020	49-2021	Radio, Cellular, and Tower Equipment Installers and Repairers
7020	49-2022	Telecommunications Equipment Installers and Repairers, Except Line Installers
7030	49-2091	Avionics technicians
7040	49-2092	Electric motor, power tool, and related repairers
7100	49-2094	Electrical and Electronics Repairers, Commercial and Industrial Equipment
7100	49-2095	Electrical and Electronics Repairers, Powerhouse, Substation, and Relay
7120	49-2097	Audiovisual equipment installers and repairers
7130	49-2098	Security and fire alarm systems installers
7140	49-3011	Aircraft mechanics and service technicians
7200	49-3023	Automotive service technicians and mechanics

Census Code	SOC Code	Occupation Title
7210	49-3031	Bus and truck mechanics and diesel engine specialists
7220	49-3041	Farm Equipment Mechanics and Service Technicians
7220	49-3042	Mobile Heavy Equipment Mechanics, Except Engines
7220	49-3043	Rail Car Repairers
7240	49-3051	Motorboat Mechanics and Service Technicians
7240	49-3052	Motorcycle Mechanics
7240	49-3053	Outdoor Power Equipment and Other Small Engine Mechanics
7300	49-9011	Mechanical Door Repairers
7300	49-9012	Control and Valve Installers and Repairers, Except Mechanical Door
7315	49-9021	Heating, air conditioning, and refrigeration mechanics and installers
7330	49-9041	Industrial Machinery Mechanics
7330	49-9045	Refractory Materials Repairers, Except Brickmasons
7350	49-9043	Maintenance workers, machinery
7360	49-9044	Millwrights
7420	49-9052	Telecommunications line installers and repairers
7430	49-9061	Camera and Photographic Equipment Repairers
7430	49-9062	Medical Equipment Repairers
7430	49-9063	Musical Instrument Repairers and Tuners
7430	49-9064	Watch Repairers
7430	49-9069	Precision Instrument and Equipment Repairers, All Other
7340	49-9071	Maintenance and repair workers, general
7640	49-9093	Other installation, maintenance, and repair workers
7540	49-9094	Locksmiths and safe repairers
7560	49-9096	Riggers
7640	49-9099	Other installation, maintenance, and repair workers
7700	51-1011	First-line supervisors of production and operating workers
7730	51-2031	Engine and other machine assemblers
7740	51-2041	Structural metal fabricators and fitters
7810	51-3021	Butchers and Meat Cutters
7810	51-3022	Meat, Poultry, and Fish Cutters and Trimmers
7810	51-3023	Slaughterers and Meat Packers
7905	51-4011	Computer-Controlled Machine Tool Operators, Metal and Plastic
7905	51-4012	Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic
8030	51-4041	Machinists
8130	51-4111	Tool and die makers
8250	51-5111	Prepress technicians and workers
8610	51-8021	Stationary engineers and boiler operators
8620	51-8031	Water and wastewater treatment plant and system operators
8640	51-9011	Chemical Equipment Operators and Tenders
8640	51-9012	Separating, Filtering, Clarifying, Precipitating, and Still Machine Setters, Operators, and Tenders
8910	51-9194	Etchers and engravers
9650	53-7071	Gas Compressor and Gas Pumping Station Operators
9650	53-7072	Pump Operators, Except Wellhead Pumps
9650	53-7073	Wellhead Pumpers