Stackable Credential Pipelines in Ohio

Evidence on Programs and Earnings Outcomes—Technical Appendix

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About This Appendix

This appendix supplements the report *Stackable Credential Pipelines in Ohio: Evidence on Programs and Earnings Outcomes*, available at www.rand.org/t/RRA207-1. Here, we provide more details about the data and empirical approach, additional information about the samples, and some alternative results from analyses related to those that appear in the main report.

RAND Education and Labor

This study was undertaken by RAND Education and Labor in partnership with the Ohio Department of Higher Education. RAND Education and Labor is a division of the RAND Corporation that conducts research on early childhood through postsecondary education programs, workforce development, and programs and policies affecting workers, entrepreneurship, and financial literacy and decisionmaking. This study was sponsored primarily through funding from the U.S. Department of Education's Institute of Education Sciences, including grant number R305H190033 to the RAND Corporation ($399,853). Funding from the ECMC Foundation ($280,543) also helped support early work that laid the groundwork for this report. The opinions expressed in this report are the authors' alone and do not represent the views of the Institute of Education Sciences or the ECMC Foundation.

More information about RAND can be found at www.rand.org. Questions about this appendix should be directed to Lindsay Daugherty at ldaugher@rand.org, and questions about RAND Education and Labor should be directed to educationandlabor@rand.org.

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Abbreviations

CIP	Classification of Instructional Programs
HEI	Higher Education Information
IT	information technology
MET	manufacturing and engineering technology
OTC	Ohio Technical Center

1. Data Sources

As mentioned in the main report, we link together several data sources. The first is a collection of certificate program applications for approval, described in more detail in Chapter 2 of this appendix.

The second source is a comprehensive record of every student enrollment and graduation from all public community colleges and universities in Ohio, provided by the Ohio Department of Higher Education's Higher Education Information (HEI) System. The third source is an analogous record for student enrollment and credential completion at Ohio Technical Centers (OTCs). The HEI and OTC data are housed in the Ohio Longitudinal Data Archive (see Ohio Longitudinal Data Archive, undated). Some yearly trends in degree completion from both of these data sources are discussed in depth in a prior report (Daugherty et al., 2020a; Daugherty et al., 2020b). Both data sets were available for school years 2004–2005 through 2018–2019.

The fourth source, which was not used in our prior report, is a comprehensive record of employment and wages at jobs eligible for unemployment insurance in Ohio. According to the U.S. Bureau of Labor Statistics, "self-employed workers, unpaid family workers, workers in certain not-for-profit organizations, and several other small (primarily seasonal) worker categories are not covered" by unemployment insurance systems, and, therefore, they are not part of our data set (U.S. Bureau of Labor Statistics, 2014, p. 14). The employment and wage data were available from the third quarter of 2000 through the second quarter of 2019.

We used a unique code to merge the three data sets and create a panel in which individuals can be observed over time. The code is based on the Social Security number, which is scrambled and replaced with a unique code before the data sets are shared with researchers. The code is missing for less than 1 percent of the degree-earner records in the HEI data and for about 4 percent of the clock-hour certificate-earner records in the OTC data. Therefore, our linked database is broadly representative of the population of students attending public postsecondary institutions in Ohio.

How Data Access Shaped Our Analytical Approach

Our analysis had two aims, each of which had unique data needs. The analysis of certificate programs offered in Ohio relied on program applications. Only a small set of those could be linked to administrative records using a program code, partly because the final code often was not present at the time of the application. We therefore focused on the program characteristics listed in the applications. Ideally, we could view not only the way the program was proposed but how and when it came into being and how it was scaled up. State leaders interested in learning more about stackable pipelines should attempt to gather and centralize these data on certificate programs.

Timing information is crucial for this type of research. If researchers knew about the rollout of changes across schools and cohorts of students, then they could construct a plausible set of comparison schools and cohorts to infer the effect of introducing policy changes.

Our analysis of student earnings was supported by a robust and comprehensive data set in Ohio. State leaders interested in this type of research should look to Ohio as an example of a state that linked together data from multiple systems, sourced from dozens of postsecondary institutions from the state's unemployment insurance system. Furthermore, the state made this data available to researchers through a clear and low-cost process that emphasized the protection of student privacy and confidentiality. Our main limitation, therefore, was not a data issue but the inability to run a controlled scientific experiment in which stacked credentials are distributed across the population without being caused by other underlying factors that are also associated with students' earning potential. Such an experiment would be all but impossible, but we attempted to approximate it using the methods described in the next chapters. We also describe the limitations of our approach and some feasible alternatives.

2. Details on the Program Analysis

Data and Sample Selection for Program Approvals

Starting in 2014, institutions that wanted to offer new technical certificate programs were required to submit an application form to the Ohio Department of Higher Education describing the new program, how it would operate, and what student and employer needs it would meet. These application forms were required of both clock-hour and credit-bearing certificate programs. There was very little missing data, although the responses on the program application form might not completely or accurately reflect the circumstances of the program in its final form. These data identify programs that colleges designed and intended to offer, although not all of the programs were actually approved or offered. Some of them had specific program codes that we could verify using the HEI database, but the majority did not at the time of application.

Among the new programs, there were several key measures. We were able to sort the programs by field, and our fields of interest represented 55 percent of the programs, similar to the proportion that these fields represented among granted certificates in the HEI system. The analysis sample included 415 programs with application dates from 2014 through 2019. The programs were 19 percent clock-hour certificates, 60 percent short-term certificates, and 21 percent long-term certificates. They were 38 percent health care, 43 percent manufacturing and engineering technology (MET), and 19 percent information technology (IT) (weighted not by number of degrees but by number of unique programs).

We selected seven program features that most closely aligned with those that were reported in the literature as features of stackable credential programs. In particular, the questions on the approval form asked whether the program was part of articulation and transfer agreements, was developed in collaboration with industry, was connected to particular licensures, included experiential learning, and assisted students with transitions. Selected measures from the approval form are listed in Table 2.1.

Table 2.1. Selected Prompts from Program Approval Form

Topic	Question
Identify program	Name Program code (if available)
Field or type	CIP (Classification of Instructional Programs) code Clock-hour or credit-hour Short (less than one year) or long (one year)
Connection to degree program, year	Is this certificate embedded in a degree program that is approved or pending approval? Provide name of degree and year submitted for approval.
Articulation/transfer	Select the Ohio Department of Higher Education articulation and transfer initiatives in which this certificate program and its related courses are participating: approved/pending career-technical credit transfer, one year option eligibility, other. What bi-lateral articulation agreements, if any, are active for this program? What bi-lateral articulation agreements are being pursued?
Links to industry	Does the institution consult with business and industry regarding the program? Describe or provide evidence. Identify the occupational license(s) or industry certification(s) on the approved list that your students could earn related to this program. Or provide rationale for not relating to an industry license or certification.
Activities	Is experiential learning a component of the program? Please describe.
Assistance and support	Describe how your institution assists students with transition into the workforce or the continuation of their education leading to a degree program.

3. Details on the Earnings Analysis

Sample Selection for Earnings Analysis

Our research questions regarding the benefits of stacking credentials require a strategy to compare individuals' earnings before and after they attain postsecondary credentials, and our primary focus is on students stacking credentials after having earned an initial certificate in health care, MET, or IT. We therefore made four primary restrictions on the merged data set.

First, we selected certificate-earners. For OTC records, we selected individuals who had earned an industry credential (a clock-hour certificate). For HEI records, we selected individuals who had earned either a short-term certificate (requiring less than one year of full-time enrollment) or a long-term certificate (requiring one or more years).

Second, we restricted our analysis to the three fields. Those fields account for 58 percent of all first certificates during our study period. Rates of stacking were comparable between MET; IT; other fields, such as business administration; and the overall average outside health care, around 55 percent. Within health care, the rate of stacking was lower, at 35 percent. However, health care is the single largest field, on its own accounting for 45 percent of certificates.

Third, we selected a period during which a student must have received the certificate, which allowed us to observe significant pre-certificate earnings as well as post-certificate credential-stacking and earnings. Our sample focused on students who earned their first certificate during school years 2004–2005 through 2012–2013. This allowed for up to five years of pre-certificate data and up to six years of post-certificate data.

Fourth, we required that students have positive earnings in at least four quarters before the quarter in which they earned their first certificate. Removing students without a pre-certificate earnings history reduced the number of unique individuals by 12 percent (mainly removing younger individuals with less of a pre-certificate work history) and reduced the number of student-quarter observations with earnings by 5 percent. The final database included a total of 28,239 individuals observed for a total of 978,211 student-quarters of earnings (an average of 35 total quarters per student, out of a possible 45). Several of our analyses limit the sample according to student characteristics or the type and field of the initial certificate. Those sample sizes appear in Table 3.1.

The only measure with missing data was age among students who initially earned certificates at the OTCs. For 77 percent of those students, we cannot measure age or adult-learner status. We describe later how this affects our regression analysis, but those individuals generally remain in the data set unless the analysis is specifically grouping individuals by adult-learner status.

Table 3.1. Sample Sizes and Quarter Counts in Subgroups

Subgroup	Unique Individuals	Student-Quarter Observations
Total	28,239	978,211
By type		
OTC	4,761	157,676
Short-term certificate	10,567	361,991
Long-term certificate	12,911	458,544
By field of study		
Health care	21,937	763,081
MET	4,901	167,940
IT	1,401	47,190
By type and field of study (large groups for which we estimate results)		
OTC, health care	4,369	145,971
Short-term, health care	7,156	246,056
Short-term, MET	2,414	82,818
Short-term, IT	997	33,117
Long-term, health care	10,412	371,054
Long-term, MET	2,191	76,370
Long-term, IT	308	11,120
By gender		
Women	18,380	636,422
Men	9,859	341,789
By race and ethnicity (large groups for which we estimate results)		
White	23,407	812,969
Black or African American	2,526	87,162
Hispanic	434	15,188
By age		
Young adult (under 25)	7,918	271,342
Adult learner (ages 25 and older)	16,615	584,799

SOURCE: Author calculations based on HEI and OTC data in the Ohio Longitudinal Data Archive.

Measures for the Earnings Analysis

All of the data definitions for our measures in the employment analysis are straightforward. These definitions are as follows:

- *Fields*: Ohio classifies each credential using the CIP coding system. We define *health care fields* as those with a two-digit CIP code of 34 (Health-Related Knowledge and

Skills), 51 (Health Professionals and Related Clinical Sciences), or 60 (Residency Programs). We define *MET fields* as those with a two-digit CIP code of 14 (Engineering), 15 (Engineering Technologies/Technicians), or 48 (Precision Production). We define *IT fields* as those with a two-digit CIP code of 11 (Computer and Information Sciences and Support Services).

- *Stacked credential*: We define a *stacked credential* as any credential earned at Ohio public institutions after the initial certificate. That includes credentials earned in the same school year, and it includes OTC certificates, short-term certificates, long-term certificates, associate's degrees, and bachelor's degrees. Among stackers, we observe the field and level of stacking to define alternative outcome measures. *Field* is defined in exactly the same way as it is for certificates. *Progressive stacking*, or stacking to the next level, refers to individuals who start with a certificate and go on to stack credentials up to the degree level or individuals who start with a noncredit certificate and go on to stack to any credit-bearing certificate or degree.
- *College enrollment*: Our analysis uses calendar quarters. In the OTC data, we count a student as having college enrollment in a quarter if the student is enrolled in a course—of any type, intensity, or length—with dates that overlap with part of the quarter. In the HEI data, we map academic terms onto quarters: Winter, spring, summer, and fall map onto quarters one through four, respectively. This matching is not exact, depending on the dates that each college uses to start and end terms.
- *Earnings*: Earnings are counted in constant 2019 dollars and are counted only among student-quarter records with some positive earnings. Earnings represent the total earnings across all jobs in the unemployment insurance system.
- *Middle-class income*: This is a binary indicator for having earnings higher than 200 percent of the federal poverty guideline for a single-person household in the lower 48 states in that calendar year (Office of the Assistant Secretary for Planning and Evaluation, 2021).
- *Student characteristics*: Students self-report gender, race, and ethnicity from a set of predetermined categories. The race categories are white, black or African American, and Hispanic of any race (all of which constitute large-enough groups that we include percentages in the report), as well as Asian, Native Hawaiian or other Pacific Islander, American Indian or Alaska Native, two or more races, and nonresident alien (many of which are small groups that are too limited to do robust analysis on). The categories for gender are men and women. We define *adult learners* as students who are 25 or older when they earn their first certificate.

Our definition of stacking is more inclusive than that used in a study of California data (Bohn, Jackson, and McConville, 2019). The researchers grouped concurrent credentials together into the first certificate rather than counting them as stacks. Among stackers in our data, 61 percent who began with OTC certificates earned additional credentials in the same academic year, although not necessarily concurrently. Among short-term and long-term certificate-earners who stacked, 19 percent and 16 percent did so in the same academic year in which they earned their initial certificate. The California study ignored students who transferred to universities. In our study, we counted bachelor's degrees as a kind of stack, although this is rare in our data. The

California study counted a second credential as a stack only if it was in the same broad academic field, while we considered all fields, and we report stacking within a field as a separate analysis.

Our scope is different in some ways from that of a study of stackable credentials in Virginia (Meyer, Bird, and Castleman, 2020). In that study, the researchers considered a broader group of potential stackers by including students who first earned an associate's degree. They also narrowed their focus to adult learners and ignored earnings in the period between the first credential and later credentials. We included younger students as long as they had a work history, and we included earnings for students throughout their education, controlling for current enrollment. Neither the Virginia study nor the California study included individuals who earned noncredit postsecondary certificates.

All three studies used the same general model, requiring data on a sufficient past earnings history to establish a baseline and then estimating a percentage increase in earnings for each individual. The next section provides details on this model.

The Regression Model for the Earnings Analysis

As noted in the main report, we estimate a regression of log earnings on credentials, then adjust the estimates to provide effects in terms of a percentage change over a person's past earnings. To isolate the effects of credentials, the regression controls for several factors that potentially affect earnings and that might be associated with credentials and education. We include an indicator ($Enrolled_{iq}$) for any college enrollment at an OTC, community college, or public university in the quarter to control for the potential decrease in earnings while students are taking postsecondary courses. To control for factors common to all individuals, such as prevailing economic trends, we include a set of indicators (β_q) for quarters. These refer to the calendar quarter, such as the first quarter of 2007.

Because we have multiple observations for each individual, we include a fixed effect (α_i) (indicator for that individual) to control for any observable or unobservable but unchanging factors affecting that individual's earnings. When we explore differences by static individual characteristics, such as race or the field of the first certificate, we run separate regressions in those subsamples. At the individual-quarter level, we include a measure of age as indicators (i.e., for being 27, 28, etc.). One of the indicators represents missing age, which is the case in all quarters for 77 percent of OTC certificate-earners. ε_{iq} is an idiosyncratic error term.

The resulting equation can be expressed as follows:

$$\ln(Earnings_{iq}) = \alpha_i + \beta_q + \delta Age_{iq} + \rho Enrolled_{iq} + \gamma AfterCert_{iq} + \eta AfterStack_{iq} + \varepsilon_{iq} .$$

The subscripts denote an individual i and a quarter q. The coefficients (represented by Greek letters) capture the relationship between the independent variables and the dependent variable. A set of coefficients δ captures the effects at different ages, ρ is the effect of college enrollment, γ

is the effect on log wages after the initial certificate is earned, and η is the effect on log wages after a stack is earned. We focus on the effects of certificates and stacking. These effects average together periods after credentials and compare them with prior periods.

We transform the log-linear coefficients to represent the percentage change as follows:

Percentage increase in earnings after cert = $\exp(\gamma) - 1$
Percentage increase in earnings after first stack = $\exp(\gamma + \eta) - 1$.

We also estimate the effect on earnings of some narrower definitions of stacking, such as within the same field and to a progressively higher level. The equation for these analyses is as follows:

$$\ln(Earnings_{iq}) = \alpha_i + \beta_q + \delta Age_{iq} + \rho Enrolled_{iq} + \gamma AfterCert_{iq} + \eta_1 AfterStack_{iq} + \eta_2 AfterStackType_{iq} + \varepsilon_{iq}.$$

In the above equation, the change in log wages after the stack is among the students who did not achieve the focal stack type (e.g., did not stack within the field of their certificate). The change in log wages after the stack type is the bonus associated with achieving that stack type, as follows:

Percentage increase in earnings after cert = $\exp(\gamma) - 1$
Percentage increase in earnings after stack of any type = $\exp(\gamma + \eta_1) - 1$
Percentage increase in earnings of focal stack type = $\exp(\gamma + \eta_1 + \eta_2) - 1$.

Assumptions and Limitations of the Regression Model

The primary obstacle to estimating the returns from stacking is that unobserved factors might drive wage returns and might also drive individuals to stack credentials. Without adequately controlling for these unobserved factors, we might assign too much importance to credentials in explaining wages.

For example, an individual who stacked might be more productive and motivated in his or her chosen field relative to other students who received only a certificate. That individual might stack additional credentials and earn higher wages. Without a measure of motivation, we cannot tell how much the additional credentials caused wage increases or say that the wage increases seen during this individual's career would accrue to other, less motivated individuals if they just stacked credentials.

To attempt to overcome this obstacle, we make within-individual comparisons of log wages over time and then compare changes across individuals who did or did not stack credentials. Furthermore, we include controls for each period, so that the comparisons are among individuals who stacked at a particular quarter versus other similar students—all of whom started with certificates in Ohio—who did not stack in that quarter but might have stacked earlier or gone on to stack later. This is accomplished by the inclusion of individual and quarter fixed effects. The individual fixed effects control for anything that is constant about an individual over time and that contributes to wages, such as relatively higher motivation or other static characteristics. The quarter fixed effects control for anything that is constant across individuals in a particular quarter, such as economic trends in the state.

The intuition for this model is similar to a difference-in-differences analysis. To interpret the estimates as the effect of stacking credentials, we assume that the wage growth in quarters and for individuals with no stacking is a good proxy for that of the stacking group had they not earned a credential in that quarter. This assumption is called *parallel trends* in wages. This assumption would fail if students who stacked were to have higher wage *growth* than others, not only higher wages overall, even without stacking credentials, and were to experience it in exactly the quarters following a particular point in time. Because any evaluation of this assumption relies on the counterfactual scenario of what stackers would have experienced had they not stacked, it is impossible to know for sure whether this assumption is valid.

One way to provide support for this assumption is to check for parallel wage growth across groups before stacking occurred. Figures 4 and 5 in the main report show nearly parallel wages in the period before the first certificate, across all groups. After the first certificate, stacking begins to occur at different times, so there is no clear way to assess parallel pre-trends in the positive-numbered quarters post-certificate. Prior research using similar data sources to investigate similar questions has relied on the same model and assumption. See, for example, Bohn and McConville, 2018; and Meyer, Bird, and Castleman, 2020.

One alternative feasible approach is to find an instrumental variable, something that is exogenously assigned, affects stacking, and only affects wages via its effect on stacking. The instrumental variable depends on policy changes or underlying conditions, such as the distance from the student's home location to colleges. There is still an argument to be made about the plausibility of underlying assumptions (e.g., the assumption that the student's home location does not directly affect job opportunities). Another alternative would compare across states without stackable policies, but that would require both a larger scope of inquiry and additional data access that was beyond the scope of this project. Overall, the fixed-effects approach is appropriate when detailed longitudinal data are available.

Complete Regression Results

Tables 3.2, 3.3, and 3.4 report regression coefficients for the educational variables. Selected values from these tables make up the reported results in figures and tables in the main report. These coefficients are transformed into cumulative percentage changes in earnings (as described in the previous section).

These tables provide detailed information about the precision of our estimates by listing standard errors (in parentheses). The overall conclusion from these estimates is that they are generally precise, with 95-percent confidence intervals of one to five percentage points. These confidence intervals are wider in some smaller samples (see Table 3.2), such as Hispanic students.

Table 3.2. Regression Estimates and Standard Errors

Subgroup	After First Certificate		After First Stack	
	Coefficient	Standard Error	Coefficient	Standard Error
Total	0.151	(0.005)	0.160	(0.008)
By type				
OTC	0.131	(0.014)	–0.017	(0.034)
Short-term certificate	–0.013	(0.009)	0.198	(0.012)
Long-term certificate	0.301	(0.008)	0.183	(0.011)
By field of study				
Health care	0.177	(0.006)	0.200	(0.010)
MET	0.077	(0.011)	0.108	(0.015)
IT	0.003	(0.024)	0.141	(0.030)
By type and field of study				
OTC, health care	0.127	(0.014)	–0.004	(0.035)
Short-term, health care	–0.020	(0.011)	0.224	(0.015)
Short-term, MET	0.032	(0.016)	0.127	(0.020)
Short-term, IT	–0.007	(0.029)	0.158	(0.035)
Long-term, health care	0.358	(0.009)	0.252	(0.013)
Long-term, MET	0.104	(0.016)	0.100	(0.021)
Long-term, IT	0.024	(0.042)	0.157	(0.063)
By gender				
Women	0.192	(0.007)	0.195	(0.011)
Men	0.078	(0.008)	0.118	(0.012)
By race and ethnicity				
White	0.150	(0.006)	0.176	(0.009)
Black or African American	0.179	(0.018)	0.082	(0.026)
Hispanic	0.248	(0.041)	0.078	(0.062)
By age				
Young adult (under 25)	0.165	(0.011)	0.258	(0.013)
Adult learner (ages 25 and older)	0.152	(0.007)	0.114	(0.010)

SOURCE: Author calculations based on HEI and OTC data.
NOTES: Sample sizes appear in Table 3.1. Regression includes individual fixed effects, enrollment indicators, age, and quarter indicators (e.g., first quarter of 2019). Standard errors are clustered at the level of an individual.

Table 3.3. Regression Estimates and Standard Errors for Stacking to Next Level

	After Certificate		After Stack		After Stack to Next Level	
Subgroup	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Total	0.160	(0.005)	–0.023	(0.013)	0.247	(0.015)
By type						
OTC	0.133	(0.014)	–0.022	(0.034)	0.172	(0.071)
Short-term certificate	–0.003	(0.009)	0.064	(0.016)	0.204	(0.018)
Long-term certificate	0.303	(0.008)	–0.089	(0.037)	0.291	(0.038)
By field of study						
Health care	0.190	(0.006)	–0.014	(0.016)	0.297	(0.018)
MET	0.081	(0.011)	0.012	(0.025)	0.122	(0.027)
IT	0.005	(0.023)	0.001	(0.056)	0.166	(0.057)
By type and field of study						
OTC, health care	0.129	(0.014)	–0.008	(0.035)	0.167	(0.073)
Short-term, health care	–0.008	(0.011)	0.087	(0.020)	0.229	(0.024)
Short-term, MET	0.040	(0.016)	0.031	(0.030)	0.140	(0.033)
Short-term, IT	–0.005	(0.029)	0.025	(0.066)	0.156	(0.066)
Long-term, health care	0.360	(0.009)	–0.081	(0.054)	0.352	(0.055)
Long-term, MET	0.105	(0.016)	0.012	(0.050)	0.098	(0.051)
Long-term, IT	0.023	(0.042)	0.110	(0.129)	0.052	(0.136)
By gender						
Women	0.206	(0.007)	–0.062	(0.019)	0.335	(0.021)
Men	0.081	(0.008)	0.029	(0.018)	0.124	(0.020)
By race and ethnicity						
White	0.159	(0.006)	–0.010	(0.015)	0.247	(0.016)
Black or African American	0.188	(0.018)	–0.093	(0.048)	0.241	(0.053)
Hispanic	0.269	(0.041)	–0.149	(0.091)	0.357	(0.102)
By age						
Young adult (under 25)	0.171	(0.010)	0.094	(0.023)	0.203	(0.025)
Adult learner (ages 25 and older)	0.163	(0.007)	–0.078	(0.017)	0.253	(0.019)

SOURCE: Author calculations based on HEI and OTC data.
NOTES: Sample sizes appear in Table 3.1. Regression includes individual fixed effects, enrollment indicators, age, and quarter indicators (e.g., first quarter of 2019). Standard errors are clustered at the level of an individual.

Table 3.4. Regression Estimates and Standard Errors for Stacking Within a Field

	After Certificate		After Stack		After Stack Within Field	
Subgroup	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Total	0.152	(0.005)	0.035	(0.017)	0.145	(0.018)
By type						
OTC	0.131	(0.014)	0.057	(0.114)	–0.080	(0.118)
Short-term certificate	–0.013	(0.009)	0.072	(0.022)	0.153	(0.023)
Long-term certificate	0.303	(0.008)	0.040	(0.029)	0.161	(0.030)
By field of study						
Health care	0.179	(0.006)	0.053	(0.020)	0.173	(0.021)
MET	0.076	(0.011)	–0.025	(0.050)	0.143	(0.050)
IT	0.002	(0.024)	0.112	(0.053)	0.038	(0.054)
By type and field of study						
OTC, health care	0.128	(0.014)	0.130	(0.107)	–0.144	(0.112)
Short-term, health care	–0.019	(0.011)	0.094	(0.025)	0.165	(0.028)
Short-term, MET	0.031	(0.016)	–0.041	(0.063)	0.181	(0.064)
Short-term, IT	–0.008	(0.029)	0.119	(0.063)	0.052	(0.065)
Long-term, health care	0.361	(0.009)	0.063	(0.033)	0.213	(0.035)
Long-term, MET	0.104	(0.016)	0.031	(0.074)	0.075	(0.075)
Long-term, IT	0.024	(0.042)	0.153	(0.102)	0.006	(0.108)
By gender						
Women	0.193	(0.007)	0.032	(0.022)	0.189	(0.024)
Men	0.078	(0.008)	0.025	(0.028)	0.108	(0.029)
By race and ethnicity						
White	0.151	(0.006)	0.035	(0.019)	0.162	(0.020)
Black or African American	0.179	(0.018)	0.069	(0.056)	0.016	(0.060)
Hispanic	0.248	(0.041)	–0.002	(0.168)	0.088	(0.176)
By age						
Young adult (under 25)	0.167	(0.011)	0.128	(0.025)	0.158	(0.026)
Adult learner (ages 25 and older)	0.153	(0.007)	–0.029	(0.024)	0.164	(0.025)

SOURCE: Author calculations based on HEI and OTC data.
NOTES: Sample sizes appear in Table 3.1. Regression includes individual fixed effects, enrollment indicators, age, and quarter indicators (e.g., first quarter of 2019). Standard errors are clustered at the level of an individual.

Heterogeneity, by Demographics and Field

The estimates in the main report condition for field of study and for demographics because these are time-invariant measures that are a component of individual fixed effects. However, there are interactions between field of study and demographics that we explore here by estimating the base empirical model in subgroups. Because field of study can be associated with demographics (e.g., women overrepresented in health care or men overrepresented in IT), it is not clear whether the trends by field might be driven by underlying trends by demographics. The gender differences in wage increases might also vary by field. Table 3.5 contains counts of individuals by demographic groups and fields of study, and Table 3.6 contains some additional exploration of heterogeneity in wage increases by these subgroups.

When we compare the effects for women in health care with those for men in health care, the benefit of stacking is similar, but the benefit of the initial certificate is significantly lower for men. For MET, men have a much higher benefit from the initial certificate. The only field in which men and women have significantly different returns from stacking is IT, in which women have higher returns.

Comparisons by race and ethnicity within each field are similar to the overall average across fields: Returns from the initial certificate are similar or slightly lower for white students than for nonwhite students, but white students have markedly higher returns from stacking. Comparisons by age within each field are also similar to the overall average across fields. The imbalance in selection of fields is highest by gender, and, therefore, it is not surprising to see that gender differences vary by field. Race, ethnicity, and age are all more evenly distributed across fields.

Table 3.5. Sample Sizes and Quarter Counts in Subgroups for Demographics, by Field

Subgroup	Unique Individuals	Student-Quarter Observations
By gender and field of study		
Women, health care	17,540	607,652
Men, health care	4,397	155,429
Women, MET	405	13,685
Men, MET	4,496	154,255
Women, IT	435	15,085
Men, IT	966	32,105
By race, ethnicity, and field of study		
White, health care	18,250	634,637
Black or African American, health care	1,994	70,751
Hispanic, health care	325	11,556
White, MET	4,022	139,865
Black or African American, MET	418	12,715
Hispanic, MET	90	3,063
White, IT	1,135	38,467
Black or African American, IT	114	3,696
By age and field of study		
Young adult, health care	9,569	176,497
Adult learner, health care	8,979	474,037
Young adult, MET	2,307	44,928
Adult learner, MET	2,361	116,072
Young adult, IT	527	9,138
Adult learner, IT	790	35,469

SOURCE: Author calculations based on HEI and OTC data.
NOTE: Data on Hispanic students in IT are not included because of the small sample size.

Table 3.6. Regression Estimates and Standard Errors for Demographics, by Field

Subgroup	After First Certificate		After First Stack	
	Coefficient	Standard Error	Coefficient	Standard Error
By gender and field of study				
Women, health care	0.201	(0.007)	0.208	(0.011)
Men, health care	0.086	(0.013)	0.166	(0.021)
Women, MET	–0.003	(0.044)	0.062	(0.058)
Men, MET	0.084	(0.012)	0.113	(0.015)
Women, IT	0.012	(0.043)	0.167	(0.060)
Men, IT	–0.006	(0.028)	0.132	(0.035)
By race, ethnicity, and field of study				
White, health care	0.176	(0.007)	0.221	(0.011)
Black or African American, health care	0.209	(0.020)	0.103	(0.030)
Hispanic, health care	0.316	(0.047)	0.159	(0.084)
White, MET	0.081	(0.012)	0.112	(0.016)
Black or African American, MET	0.073	(0.049)	0.039	(0.061)
Hispanic, MET	0.067	(0.082)	0.111	(0.080)
White, IT	–0.006	(0.026)	0.154	(0.033)
Black or African American, IT	0.028	(0.096)	0.074	(0.112)
By age and field of study				
Young adult, health care	0.196	(0.012)	0.300	(0.016)
Adult learner, health care	0.188	(0.009)	0.157	(0.013)
Young adult, MET	0.119	(0.021)	0.060	(0.026)
Adult learner, MET	0.042	(0.014)	0.082	(0.018)
Young adult, IT	–0.030	(0.055)	0.225	(0.063)
Adult learner, IT	0.010	(0.028)	0.121	(0.035)

SOURCE: Author calculations based on HEI and OTC data.
NOTES: Sample sizes appear in Table 3.1. Regression includes individual fixed effects, enrollment indicator, age, and quarter indicators (e.g., first quarter of 2019). Standard errors are clustered at the level of an individual. Data on Hispanic students in IT are not included because of the small sample size.

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