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# Career Readiness in Public High Schools: An Exploratory Analysis of Industry Recognized Credentials

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WORKING PAPER No. 257-0921 • September 2021

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## Acknowledgments

We thank the Missouri Department of Elementary and Secondary Education for access to data, the Ewing Marion Kauffman Foundation, and CALDER, which is funded by a consortium of foundations (for more information about CALDER funders, see www.caldercenter.org/about-calder), for supporting this research. All opinions expressed in this paper are those of the authors and do not necessarily reflect the views of the funders, data providers, or institutions to which the author(s) are affiliated. Any errors are attributable to the authors.



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## Abstract

We use statewide administrative data from Missouri to document the prevalence of Industry Recognized Credential (IRC) programs in public high schools and understand the characteristics of students who complete IRCs. We show that 9 percent of Missouri students complete an IRC during their senior year of high school. IRC completers have lower achievement and are more likely to be disadvantaged along several measurable dimensions relative to their peers who complete analog college-ready programs, on average. Noting these average relationships, there is substantial heterogeneity among individual IRCs in terms of the types of students served: some IRCs attract students with high test scores who mostly go on to attend college, whereas others serve low-scoring students who mostly forego college. There is strong gender segregation across individual IRCs that aligns with gender segregation across occupations in the labor market.

## 1. Introduction

Nearly every state in the U.S. has adopted standards with the stated goal of ensuring that all K-12 students are on track for "college and career readiness". The language surrounding these standards—be it from the federal government or state education agencies—puts readiness along both dimensions on equal footing.[1] However, the research literature to date has disproportionately focused on the "college readiness" aspect of these standards and in comparison, paid scant attention to K-12 programs focused on "career readiness".

The emphasis in research on college readiness is not surprising and is likely attributable to several factors. First, "college readiness" programs in U.S. high schools—e.g., advanced placement and dual credit/enrollment programs—are larger and serve more students than career-oriented programs (we provide some evidence on this below). Second, education researchers are themselves highly educated, and through revealed preference have a clear interest in the pursuit of higher education. This may lead them to gravitate toward the study of interventions tied to increased schooling. Third, a practical consideration is that evaluations of "college readiness" programs are more appealing because K-12 and postsecondary data linkages are increasingly common. In contrast, data linkages between K-12 and the labor market are often unavailable (and in many states currently do not exist), making evaluations of "career readiness" K-12 programs challenging due to a lack of outcome data.

All of that said, the overwhelming research focus on "college readiness" ignores the large fraction of high school graduates who do not participate in postsecondary education directly from K-12 schools—just over 30 percent in recent years (de Brey et al., 2021). To serve these students effectively, along with the many initial college enrollees who do not earn degrees

[1] For instance, see the U.S. Department of Education's college- and career-readiness standards, retrieved 06.03.2021: https://www.ed.gov/k-12reforms/standards

(raising questions about how much they ultimately benefit from attending college), K-12 schools would benefit from more information about which students participate in career-training programs and how they are impacted. However, the dearth of research on "career readiness" programs is such that outside of a small literature focused on intensive career and technical education (CTE) programs, there is little evidence on which to draw to understand career-readiness opportunities in K-12 schools.

We begin to address this gap in the literature by using administrative microdata from Missouri to study Industry Recognized Credential (IRC) programs. IRCs are awarded to students who demonstrate competency in a specific career area through participation in a career-training experience or by earning an adequate score on a technical skills examination. IRCs can be obtained as part of an intensive CTE program but can also be pursued in a one-off fashion in the same way a student might take a single advanced placement course without enrolling in a full-scale honors program. IRCs are available to high school students in most states and are offered in a variety of fields.[2]

We provide comprehensive documentation of the prevalence of IRCs and student selection into IRCs using administrative data covering all public high school students in Missouri. For frame of reference, we benchmark our findings for IRCs against more commonly-studied college-ready programs—namely, advanced placement (AP), international baccalaureate (IB), dual credit (DC), and dual-enrollment (DE) courses. We group AP and IB courses together, and DC and DE courses together, because of their substantive similarity, then compare completion patterns in AP-IB courses, DC-DE courses, and IRCs.

[2] We have confirmed IRCs are available to high school students in at least the following states: AL, AK, AR, CO, FL, GA, IN, KS, KY, LA, MD, MA, MS, MO, NJ, NM, NC, OH, OK, OR, PA, RI, SC, TN, TX, UT, VT, VA, WI, WY.

Using data from the 2018-19 school year (the last school year prior to the Covid interruption), we show that 9 percent of students in Missouri completed an IRC during their senior year of high school. Completion rates of AP-IB and DC-DE courses among high school seniors are much higher, with 19 and 31 percent completing at least one course in these programs, respectively. In terms of selection, the achievement level of the average IRC student is only slightly above the statewide mean, which stands in stark contrast to students in AP-IB and DC-DE courses, who are disproportionately drawn from the top end of the achievement distribution. Students who complete IRCs are also more likely to be disadvantaged than their peers in college-ready programs along several measurable dimensions.

In addition to making program-level comparisons, we also explore heterogeneity among the 55 different IRCs awarded in Missouri that comprise the larger "IRC program". We show that some individual IRCs attract students from the top of the achievement distribution who are very likely to attend college—examples in Missouri include IRCs in the fields of Business Management/Administration and Information Technology—while others primarily serve students with low test scores and low college attendance rates—IRCs that fit this description are most common in the fields of Architecture and Construction, Manufacturing, and Transportation and Logistics. There are also IRCs for which the student population cannot be described in such a polar fashion. For example, IRCs in education and health sciences tend to serve students who have average academic performance but are very likely to attend college. Our heterogeneity analysis makes clear that the larger IRC program represents a diverse set of educational opportunities for students with a variety of academic profiles and post-graduation intentions.

What is missing from our study is an evaluation of the efficacy of IRCs—i.e., we do not assess how these programs affect students' academic and post-graduation outcomes. As alluded to above, a lack of linked labor-market data in Missouri prevents an appropriate outcome-based evaluation.[3] Noting this limitation, our work establishes the important role of IRCs in public high school curricula and motivates the need for future work to overcome data challenges and push research forward in this area.

## 2. Background

The literature on career and technical education (CTE) focuses mostly on intensive CTE programs, most notably admittance into CTE specific high schools. Studies with the most credible causal designs find that attending a CTE high school has effects on graduation and post-graduation earnings in the range of null to positive, and sometimes substantially positive (Brunner, Dougherty, and Ross, 2021; Dougherty, 2018; Hemelt, Lenard, and Paeplow, 2019; Kemple and Wilner, 2008; Page, 2012). Effects are often concentrated among male students. We are not aware of any compelling causal studies that find negative impacts of intensive high school CTE programs on students' educational and labor market outcomes.

IRCs represent a different type of CTE experience, with a distinguishing feature being that IRCs are less intense. This is appealing from the perspective of expanding access to CTE to a broader population of high school students, and in particular to students who are interested in CTE but not a fully immersive CTE experience. There are two types of credentials that can be earned through high school IRC programs: licenses (issued by a government agency) and certifications (issued by business, trade associations, or industry).[4] The US Department of Labor (DOL) describes an IRC as being either developed and offered, or endorsed, by "a nationally-

[3] We could in principle examine the effects of IRCs on college outcomes, but to ignore labor-market outcomes in an evaluation is inconsistent with the career-oriented aspect of IRCs. We also note that missing data are not the only limitation preventing an efficacy study of IRCs. We would also need an identification strategy, but this is a moot point in the absence of appropriate outcome data.
[4] Association for Career and Technical Education, retrieved 03.22.2021: https://www.acteonline.org/wp-content/uploads/2018/02/What_is_a_Credential_71417.pdf

recognized industry association or organization representing a sizeable portion of the industry sector," or as "a credential that is sought or accepted by companies within the industry sector for purposes of hiring or recruitment…".[5] We use the term IRC to refer to credential-based programs that fit this definition taken by high-school students, as recognized by the Missouri Department of Elementary and Secondary Education (DESE).

Although IRCs existed prior to the Carl D. Perkins Career and Technical Education Act of 2006 (Perkins IV), it is this legislation that first created meaningful incentives for school districts to offer IRCs. Perkins IV provided funding for programs that (a) include rigorous academic and CTE content, with course sequences involving secondary and postsecondary education, (b) lead to an industry-recognized credential, postsecondary certificate, and/or degree, and/or (c) include dual credit/dual enrollment opportunities. Perkins IV was replaced by Perkins V in 2018, which maintains criterion (b). Thus, IRCs continue to be emphasized by federal policy and incentivized through the provision of federal funding (Malin et al., 2017).

IRCs are geared toward the 'career readiness' portion of college and career readiness (CCR) standards in U.S. public high schools, complementing an array of college-credit course programs—e.g., AP-IB and DC-DE programs—aimed at the 'college readiness' portion. Participation patterns and effects on students of college readiness programs have been studied extensively. Conger, Long, and Iatarola (2009) document disparate access to college-ready programs along the dimensions of race-ethnicity, gender, and poverty status. Studies that estimate the causal impacts of access to and participation in these programs are mixed, with some finding small positive impacts and others finding null or even negative impacts (Conger,

[5] Retrieved 03.22.2021: https://wdr.doleta.gov/directives/attach/TEGL15-10.pdf

Long, and McGhee, 2020; Hemelt, Schwartz, and Dynarski, 2020; Smith, Hurwitz, and Avery, 2017).

In contrast to the literature on intensive CTE programs, and college-ready programs, very little is known about IRC programs operating in U.S. high schools, and even less is known about their impacts on students. We are aware of just two relevant studies. First, Smiley (2018) surveys business leaders in Virginia to assess labor market demand for job candidates who have completed IRCs qualitatively. Walsh et al. (2019) provide descriptive information about IRC participation by race, age, income, and gender in Indiana, Kentucky, and Florida. These authors also describe the processes by which IRCs in these states are approved and estimate regressions linking IRC participation to wages and other student outcomes. Although these authors lack a research design to support causal inference, they find that IRC participation is positively associated with on-time graduation and post-graduation earnings, and negatively associated with bachelor's degree attainment.

## 3. Data

Our analysis is based on administrative microdata provided by the Missouri Department of Elementary and Secondary Education (DESE). We use data on the census of high school seniors enrolled in Missouri public high schools during the 2018-19 academic year. We focus on high school seniors because most IRCs are completed during the senior year.[6]

The administrative data include indicators for student race-ethnicity, gender, eligibility for free or reduced-price lunch (FRL), English language learner (ELL) status, and individualized education program status (IEP). We also use standardized test scores from the 6th grade to

[6] In a supplementary pre-analysis omitted for brevity, we find that of all IRCs completed by juniors and seniors in Missouri high schools during 2018-19, only 26 percent were completed by juniors.

document selection into program completion by achievement.[7] Post-graduation data on college enrollment for the high school seniors in our sample are available via a link to the National Student Clearinghouse (NSC). Using the NSC data in the fall immediately after the 12th-grade year—i.e., fall-2019—we place each student into one of the following postsecondary enrollment categories: (1) no college, (2) 2-year college, and (3) 4-year college. Table 1 provides descriptive statistics for our sample.

Table 2 documents student completion rates and selection into AP-IB, DC-DE, and IRC programs.[8] First, the completion rates in the top panel in column (1) show that IRCs are less commonly completed than courses in the college-ready programs. Specifically, 19 percent of Missouri high school seniors completed at least one AP-IB class and 31 percent completed at least one DC-DE class, whereas just 9 percent completed an IRC.[9] IRCs also serve a very different segment of the K-12 student population. Most notably, column (2) shows that the standardized test score for the average IRC student is just 0.10—slightly above the state average—compared to 0.65 and 0.41 for AP-IB and DC-DE students, respectively. IRC students are also much less likely to enroll in a 4-year college after high school graduation.

The bottom panel of Table 2 divides IRC students into substantive fields based on DESE classifications. The IRC fields are ordered in the table by size (i.e., total IRCs conferred). The

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[7] Ideally we could have used test scores from the 8th grade, which is the last grade of comprehensive standardized testing in Missouri. However, in the seventh and eighth grades students are split across multiple math tests (primarily the standard on-grade assessment or the Algebra-I end-of-course exam). For analytic consistency, we use test scores from the sixth grade, when virtually all students take the same on-grade test, noting that test-score levels are highly correlated for individual students during the full 3-8 grade span (Austin et al. 2020).

[8] DC and DE courses differ in that DC courses are offered at a high school by either a college-credit certified teacher or instructional television, and DE courses are offered outside of the high school on a college campus or at a local career center.

[9] The National Center for Education Statistics reports that for the class of 2019, 21.2 percent of Missouri high school graduates took at least one AP course throughout their high school career compared to the national rate of 38.9 percent. Thus, Missouri's AP course-taking rate is far below the national average. Note that the 21.2 percent figure is higher than the AP completion rate reported in Table 2, 19 percent, because the rate in Table 2 accounts for course-taking only during the senior year.

two largest IRC fields in Missouri are in Agriculture and Health Science, which are followed by Transportation and Logistics, Business Management/Administration, and Hospitality and Tourism. These five fields account for just over two-thirds of all IRCs completed by the 2018-19 cohort of Missouri high school seniors. In terms of student selection into different fields, the splits in Table 2 highlight substantial heterogeneity. The test scores and college attendance patterns of students in the Business Management/Administration field, for example, rival those of AP-IB and DC-DE students. At the other end of the spectrum, IRCs in fields such as Transportation and Logistics serve students with low test scores and low likelihoods of college attendance.

Finally, we briefly touch on the generalizability of our analysis to states outside of Missouri by examining the prevalence of common IRCs in Missouri in other states. As noted above, a handful of IRC programs account for most IRCs in Missouri and correspondingly, we focus on comparing the 10 largest IRCs in Missouri to the 10 largest IRCs in other states.[10] Table 3 shows the 10 largest individual IRCs in Missouri, ordered by the number of IRCs awarded, and how often these IRCs are among the 10 largest IRCs in other states. The largest IRC in Missouri—the Missouri Agriculture Skill & Knowledge Assessment (AGSK)—is a Missouri-specific IRC that by construction is not available in other states. The second and third largest IRCs—the Certified Nursing Assistant (CNA) and Automotive Service Excellence Certification (ASE) programs—are commonly available in other states. Several of the other largest Missouri IRCs are also available in other states, although some are specific to Missouri. From Table 3, we conclude that there is at least some degree of generalizability of our analysis, although the table

[10] This comparison is facilitated by state-level data assembled by Credentials Matter covering the 2017-18 and 2018-19 school years. Credentials Matter is a partnership between ExcelinEd and Burning Glass Technologies that aims to align labor-market demand with the credentials students earn. For more information see (link retrieved 06.02.2021): https://credentialsmatter.org/

also makes clear that there is substantial heterogeneity in the IRC landscape across states and some of our findings are likely to be Missouri specific.

## 4. Methodology

### *4.1 Student Selection into AP-IB Courses, DC-DE Courses, and IRCs*

We begin by estimating linear regression models to document completion gaps in AP-IB courses, DC-DE courses, and IRCs by various student characteristics. We estimate unconditional gaps by student race-ethnicity; gender; FRL, ELL, and/or IEP status; and achievement. Then, we estimate conditional gaps from multivariate regressions that account for all these student characteristics simultaneously. Our full regressions are similar to models used in similar applications (e.g., see Conger, Long, and Iatarola, 2009; Dougherty and Macdonald, 2020) and take the following form:

$$Y_i^j = \beta_0 + \mathbf{R_i}\boldsymbol{\beta}_\mathbf{1}^\mathbf{j} + G_i\beta_2^j + \mathbf{X_i}\boldsymbol{\beta}_\mathbf{3}^\mathbf{j} + A_i\beta_4^j + \varepsilon_i^j \tag{1}$$

In equation (1), $i$ indexes students and $j$ indexes programs. The superscript $j$ has three values—one each for completion of any AP-IB course, any DC-DE course, and any IRC—and thus equation (1) represents three different regressions, which we estimate independently. In the regressions for AP-IB and DC-DE, $Y_i^j$ is a binary indicator equal to one if student $i$ completed any course in a relevant program during her senior year. In the IRC regression, $Y_i^j$ is equal to one if student $i$ completed an IRC.

The independent variables in each equation are fixed. The variable vector $\mathbf{R_i}$ includes indicators for students' racial-ethnic designations. We compare completion rates between Asian, Black, Hispanic, White, and Other Race students, although demographics in the state of Missouri are such that the black-white comparisons are most informative. $G_i$ is a scalar set to one for female students and zero for male students. The variable vector $\mathbf{X_i}$ includes indicators for each student's status as FRL, ELL, and IEP. $A_i$ is student *i*'s test-score performance in the sixth grade, standardized to have a mean of zero and a variance of one against the full state distribution.[11] Finally, $\varepsilon_i^j$ is the error term, clustered at the school level to allow for dependence in program participation within schools.

We also augment equation (1) to include school fixed effects as follows:

$$Y_{is}^j = \alpha_0 + \mathbf{R_i}\boldsymbol{\alpha}_\mathbf{1}^\mathbf{j} + G_i\alpha_2^j + \mathbf{X_i}\boldsymbol{\alpha}_\mathbf{3}^\mathbf{j} + A_i\alpha_4^j + \delta_s + \eta_{is}^j \qquad (2)$$

Common terms in equations (1) and (2) are commonly defined. By virtue of the inclusion of the school fixed effects in equation (2), denoted by $\delta_s$, the model only identifies within-school completion gaps. This is valuable because by comparing the estimates from equations (1) and (2), we can assess the extent to which program completion gaps between different types of students are driven by cross-school or within-school differences. For example, a factor that could influence cross-school gaps in IRC completion is geographic access to off-campus IRC experiences, which could be correlated with student race-ethnicity due to residential sorting. If geography affects IRC completion, we would expect its impact to be revealed in the coefficients from equation (1), but geography cannot be factor driving the coefficients in equation (2) because it does not vary within schools.

While our clustering structure properly accounts for within-school dependence in the availability of each program, a limitation is that it does not account for *within student* dependence in program participation. In an extension, we also conduct an analysis using a

[11] In results omitted for brevity, we also use 9th-grade GPA as an alternative measure of academic performance to examine selection. Our findings are very similar qualitatively if we use GPAs instead of test scores, although test score differences between students are marginally more predictive of differences in program completion.

Seemingly Unrelated Regression (SUR) framework, which allows for correlations between the error terms across models for the same student. This modeling shift does not affect our point estimates, but it does affect the standard errors. However, because in practice the correlations within students across programs are very small, the SUR estimates—which do not account for within-school data dependency—have smaller standard errors than the estimates from the independent models with school-clustered errors.[12] In an effort to be conservative, we lead with the independent regressions and include the SUR results in the appendix. In all cases, the independently-estimated models and the SUR models lead to substantively similar conclusions.[13]

### *4.2 IRC Heterogeneity*

We also examine heterogeneity in completions of different types of IRCs among IRC students. In Table 2 above, we group IRCs into the 12 field designations used by DESE, which are themselves aggregations of 55 different individual IRCs that Missouri students completed during the 2018-19 school year. The DESE field groupings are based on the topical content of the IRCs, but often result in groupings of individual IRCs serving students with very different academic achievement and college attendance rates. For this portion of our analysis, we use data-driven tools to separate individual IRCs into different groups based on similarities in the types of students they serve rather than their topical areas.

We use *k*-means clustering to construct groups of IRCs that share commonalities in terms of the types of students served along the dimensions of test scores and college attendance rates (the sum of 2- and 4-year attendance). *K*-means clustering is an unsupervised learning technique

[12] The substantive impact of the correlations being so small is that the standard errors from the SUR regression are very similar to the standard errors one would obtain by running the regressions independently, but without clustering the errors by school.
[13] Also note that our results are substantively similar if we estimate the models using a logistic rather than linear regression framework.

that uses the following algorithm to partition groups (in our case, the 55 individual IRCs) into *k* clusters (Hartigan and Wong, 1979). First, it randomly assigns a number from 1 to *k* (to serve as initial cluster memberships) to each observation. Next, it iterates through the following two steps until the cluster assignments do not change any further.

1. Find the centroid (average point value for each variable) of each cluster. In our case, we use two variables: the proportion attending college and the average MAP test score from 6$^{th}$ grade.
2. Reassign cluster memberships for each observation to the cluster whose centroid is nearest to it based on Euclidian Distance.

We use *k*-means clustering to divide the 55 unique IRCs into three clusters (i.e., *k*=3). The clusters are ordered such that Cluster 1 includes IRCs in which students tend to have high test scores and are the most likely to attend college (specifically 4-year college), Cluster 2 includes IRCs in which students have test scores close to the state average and are less likely to attend college (and especially 4-year college), and Cluster 3 includes IRCs with students who have low test scores and are unlikely to attend college.[14]

Appendix Table A1 shows the cluster assignments for each individual Missouri IRC. Some broad patterns emerge. In terms of fields, for example, Business Management/Administration and Information Technology IRCs are concentrated in Cluster 1, whereas Architecture and Construction, Manufacturing, and Transportation and Logistics IRCs are concentrated in Cluster 3. Cluster 2, the cluster that contains the largest IRCs in Missouri, includes IRCs in Agriculture, Education, and Health Science. Other IRC fields, such as human

[14] We chose to set the cluster value at three because it provides the most intuitive and clear splits of the individual Missouri IRCs. We also considered a 2-cluster split, which essentially kept cluster 3 intact (the cluster with low test scores and college attendance) and combined clusters 1 and 2. We prefer the 3-cluster split because clusters 1 and 2 differ meaningfully in their test scores and 2-year and 4-year college going rates (see Appendix Tables A1 and A2).

services, have individual IRCs spread across all clusters. Overall, we interpret Cluster 1 IRCs as being generally the most appealing to students with strong college intentions, and Cluster 3 as being least appealing to these students, with Cluster 2 serving as a middle case with particular appeal to students interested in Agriculture, Education, and Health Science fields.

We examine selection patterns into IRCs by cluster using the same student characteristics as above. Because there are three outcome states (clusters) in this portion of our analysis, we use a multinomial logistic regression framework. We report relative risk ratios for Clusters 1 and 2 from the regressions, using Cluster 3 as the baseline condition. The relative risk ratios indicate the likelihood of completing an IRC in Cluster 1 or 2 (in the numerator) relative to the likelihood of completing an IRC in Cluster 3 (in the denominator). For example, a relative risk ratio above 1.0 for a variable associated with Cluster 1 indicates that students with that particular characteristic are relatively more likely to earn an IRC in Cluster 1 than in Cluster 3, and vice versa for values below 1.0.

## 5. Findings

### *5.1 Student Selection into AP-IB Courses, DC-DE Courses, and IRCs*

Tables 4 and 5 show results from equations (1) and (2), respectively. Each table consists of three horizontal panels, one for each program type. Output from an SUR version of the models in Table 4 is provided in Appendix Table A3.[15] As noted above, none of the substantive insights from the models are different if we estimate them within the SUR framework.

We start with the first panel of Table 4, for AP-IB courses. The unconditional model in column (1) shows that Asian students are the most likely to complete an AP-IB course, followed

[15] We do not estimate SUR models with school fixed effects because the computational demands are prohibitive, although the consistency of the estimates across the independent regressions and SUR versions of equation (1) suggest that the same would be true of equation (2).

by Hispanic, Other Race, and White students (where the latter are the omitted group)—who are all similarly likely to complete an AP-IB course—and Black students—who are the least likely to complete an AP-IB course. Column (2) shows that female students are more likely to complete an AP-IB course, column (3) shows that students who are not designated as FRL, IEP, or ELL are more likely to complete an AP-IB course, and column (4) shows that students with higher test scores in the sixth grade are much more likely to complete AP-IB courses than their lower-achieving peers.

In the final column of Table 4 we estimate a multivariate regression that includes all of the predictors simultaneously. Several of the unconditional estimates discussed in the previous paragraph shift considerably in the full model. Most notably, Black, Hispanic and Other Race students are *conditionally* more likely to complete AP-IB courses than White students, and the completion gaps by IEP and ELL status shrink to statistical insignificance. This suggests that the unconditional gaps in AP-IB completion along these dimensions are primarily driven by differences in student achievement, which is accounted for in Model 5 but not in the preceding unconditional models.[16]

The second panel of Table 4 estimates regressions of the same structure, but using DC-DE course completion as the outcome. Unlike AP-IB, White students are more likely to take DC-DE courses than all the other racial-ethnic groups unconditionally. The unconditional completion patterns in DC-DE along other dimensions largely mirror those of AP-IB—i.e., female, non-FRL, non-IEP, non-ELL, and high-achieving students are all more likely to complete DC-DE

[16] Our findings for AP-IB course completion gaps by race-ethnicity in Table 4 align with existing evidence from Conger, Long, and Iatarola (2009) and Conger, Long, and McGhee (2020). Moreover, the finding that Black students are unconditionally underrepresented in AP-IB courses, but conditionally overrepresented, is consistent with related evidence on Black-White gaps in college attendance and completion (Arcidiacono and Koedel, 2014; Cameron and Heckman, 2001).

courses. Conditionally, the racial-ethnic completion gaps in DC-DE moderate, although they remain negative or null in all comparisons with White students. Female, FRL, IEP, and ELL students are also all conditionally less likely to complete a DC-DE course, although the conditional gaps are muted relative to the unconditional gaps. Test scores strongly predict DC-DE completion in the unconditional and conditional models.

The third and final panel of Table 4 shows the results for IRCs. The first thing to notice is that the regression coefficients are generally much smaller in magnitude in both the unconditional and conditional models compared to the models for AP-IB and DC-DE courses. This is driven in part by the lower IRC completion rate relative to AP-IB and DC-DE (per Table 2), which makes all of the coefficients smaller, but this is not the full explanation—there is also less student selection into IRCs along most dimensions.

The largest dimension along which there is meaningful selection into IRCs is race-ethnicity. Both the unconditional and conditional models show that White students are the most likely to compete IRCs. In fact, the racial/ethnic completion gaps by race-ethnicity do not attenuate at all moving from the unconditional to conditional model. Compared to their White peers, students from the other racial-ethnic groups are 3-6 percentage points less likely to complete IRCs. The conditional IRC gap between Black and White students—6 percentage points—is of the same magnitude as the conditional gap in DC-DE course completion, but larger as a percentage of the baseline participation rate.

However, selection along other dimensions into IRCs is much smaller or nonexistent. The only significant IRC completion gap is along the dimension of IEP status, where IEP students are 3-4 percentage points less likely to complete an IRC than their non-IEP peers. Notably, the association between student test scores and IRC completion is negligible, both unconditionally and conditionally, which reinforces the point from the descriptive statistics above that there is not meaningful selection into IRC completion by student achievement, on average. The results in columns 2-4 also explain why the racial-ethnic gaps in IRC completion do not attenuate in the full model—there is no scope for the conditioning variables to attenuate the gaps (because they are not strong predictors of the IRC completion unconditionally).

Next, we compare the estimates from equation (1) in Table 4 to analogous estimates from equation (2) in Table 5. Recall that the difference between these estimates stems from the inclusion of school fixed effects in equation (2), which isolate within-school differences in program completions. The most useful way to interpret each estimate in Table 5 is relative to its analog in Table 4. If the coefficients in Tables 4 and 5 are the same, it means that the completion gaps by student characteristics are driven entirely by *within-school* differences—i.e., when the model isolates only within-school differences in completion via the school fixed effects (in equation 2), the differences are just as large as if it captures both within- and across-school differences (in equation 1). At the other extreme, if the coefficients in Table 5 are all zero, it would indicate that all differences in completion by student characteristics in Table 4 are driven by *across-school* differences. The in-between case, in which the coefficients in Table 5 are attenuated relative to Table 4, but not zero, would imply that a mix of *within- and across-school* differences in completions drive the total gaps.[17]

Comparing the results in Tables 4 and 5, the coefficients on student gender, FRL status, IEP status, ELL status, and the test score are nearly unchanged in both the unconditional and conditional models. While perhaps surprising in some instances, this makes clear that the

[17] A fourth possibility is that the coefficients in Table 5 could be larger than in Table 4—nominally this happens for a few of the small coefficients, but there are no substantive changes in the coefficients in this way (if there were, it would imply odd student sorting patterns).

completion gaps that exist along these dimensions are driven entirely by within-school differences between students. In contrast, the racial-ethnic differences for each program in Table 5 are generally muted relative to Table 4, especially for Asian and Black students relative to White students. This means that the total completion gaps by race-ethnicity are the product of both within- and across-school differences, suggesting that student sorting to schools—presumably driven largely by residential segregation—partly contributes to the completion gaps.

In summary, we find that selection into IRCs along most dimensions is small to non-existent, with the exception of race-ethnicity. This stands in stark contrast to the AP-IB and DC-DE programs, where selection along non-race dimensions is substantial. Along the dimension of race-ethnicity, selection into IRCs is such that White students are overrepresented relative to all other racial-ethnic groups. The direction and magnitude of selection into IRCs by race-ethnicity is a close match to that of DC-DE; alternatively, for AP-IB courses, selection is such that conditional on other characteristics, White students are significantly underrepresented. The gaps in IRC completions by race-ethnicity are due to both across- and within-school factors.

### *5.2 IRC Heterogeneity*

Table 6 shows estimates from our multinomial logistic regressions that predict students' cluster assignments among the sample of students who complete an IRC. The relative risk ratios show IRC completion likelihoods relative to Cluster 3. Recall that Cluster-3 IRCs serve students with low achievement and who are unlikely to attend college (e.g., 80 percent of Cluster-3 students are not enrolled in college in the fall after high school graduation). Ratios above 1.0 indicate that students with the given characteristic are relatively more likely to complete an IRC in the focal cluster than in Cluster 3, and values below 1.0 indicate the reverse. Statistical significance for all risk ratios is assessed against a value of 1.0 based on the underlying output from the multinomial regression, where a value of 1.0 implies no differential selection between the focal cluster and Cluster 3 along the relevant dimension.

A general limitation of this portion of our analysis is that it is underpowered relative to the preceding analysis conducted at the program level. This is because our sample size in this section is much smaller—we estimate the models on just the 9 percent of our sample that completed an IRC. As a consequence, some patterns in IRC participation across clusters are estimated too imprecisely to permit strong inference.

Noting this caveat, some pronounced patterns in IRC participation across clusters are detectable by our analysis. The most obvious of these is that student test scores are strong predictors of the IRC cluster, which is by construction because we use student test scores in the *k*-means algorithm to assign the clusters. More substantively, a significant dimension of sorting in the clustered analysis is by gender. Women and men are spread highly unevenly across the clusters. Women are most prevalent in Cluster 2, followed by Cluster 1, followed by Cluster 3; and vice-versa for men. This is particularly interesting given that there is almost no selection into IRC completion by gender overall, per Tables 4 and 5. The implication is that women and men are similarly likely to complete an IRC, but are sorted strongly into different types of IRCs. Looking at the content categories represented in each of the clusters is instructive about the gender gaps. Cluster 3 IRCs are mostly made up of programs in Transportation and Logistics, Manufacturing, and Architecture and Construction. In these fields, men make up almost the entire workforce. In contrast, two of the largest IRC content categories in cluster 2 are Health Science and Education, fields in which women are overrepresented in the workforce.[18]

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[18] See labor force statistics from the current population survey provided by the Bureau of Labor Statistics (link retrieved on 06.02.2021): https://www.bls.gov/cps/cpsaat09.htm. These findings are consistent with related evidence from Dougherty and Macdonald (2020), who examine participation gaps across fields among STEM-oriented CTE

In addition to the strong gender sorting across IRC fields, several other patterns emerge in Table 6. FRL students are more prevalent in Cluster 3 than in Cluster 1 or Cluster 2, compared to their non-FRL peers. Similarly, IEP students are less likely to complete a Cluster-1 or Cluster-2 IRC, although like in the preceding analysis, the gaps by IEP status decline markedly in the full model, which suggests that test-score gaps between IEP and non-IEP students account for most of the differences. Finally, there is suggestive evidence of sorting across clusters by race-ethnicity. Our most informative racial-ethnic comparison between Black and White students suggests that Black students are conditionally overrepresented in Cluster 1 and underrepresented in Cluster 2 relative to Cluster 3, compared to their white peers.

## 6. Discussion and Conclusion

Using administrative microdata from Missouri, we show that participation in IRCs is smaller than in more commonly studied "college ready" analog programs, but still large. In 2018-19, 9 percent of Missouri high school seniors completed an IRC. Despite the prevalence of IRCs in high school curricula in Missouri and other states, and the clear emphasis on career-ready education in policy documents at all levels of government in the U.S., the research literature on IRCs is virtually non-existent. Exemplifying the dearth of research, we suspect that IRC participation has increased substantially in U.S. high schools over the past decade, but we could not find any documentation—published in academic articles or otherwise—to confirm or refute this claim. Major compendiums of education statistics, such as the U.S. Department of Education's Digest of Education Statistics (de Brey et al., 2021), make no mention of IRCs.

Our study provides detailed documentation of IRC completion patterns in Missouri. We show that students who complete IRCs have very different profiles than their peers in college-

programs in Massachusetts and conclude that field participation patterns by gender mirror field imbalances in the labor market.

ready programs. The college-ready programs primarily serve students with high test scores and who are more advantaged than other students as measured by FRL status, IEP status, and ELL status; in contrast, there is virtually no selection into IRCs along these dimensions. Similarly, there is no selection into IRCs by gender (overall). The only observed dimension along which IRC completion gaps exist is by race-ethnicity—White students are more likely to complete IRCs than students in other racial-ethnic groups. On the whole, our findings make clear that IRCs serve a much broader population of high school students than the college-ready programs that have received the bulk of attention in research.

Within the larger "IRC program," our analysis of individual IRCs reveals considerable heterogeneity among them. Some IRCs attract high-achieving students with clear college intentions, while others attract students with low test scores who primarily enter the workforce directly from high school. There is also strong gender segregation across IRCs. The gender segregation is broadly consistent with gender segregation in related occupations in the labor market—e.g., many of the male- and female-dominated IRCs are tied to work in fields that are similarly male- and female-dominated.

The remaining research question that we would have liked to address, "How does IRC participation affect students' labor market outcomes?" cannot be answered in Missouri because the data infrastructure does not exist to follow students from K-12 education into the workforce. The Missouri data represent a substantial improvement over historically available data on IRCs (Castellano, Stone III, and Stringfield, 2005) and they permit thorough documentation of the IRC landscape in Missouri high schools from a usage-based perspective. However, without linked labor-force data, our analysis must remain silent on the efficacy of IRC programs in terms of producing desirable outputs (e.g., higher student employment and wages). We hope that future data linkages in Missouri, and/or linkages in other states, will facilitate a continuation of this research to examine if and how students benefit from participation in IRC programs.

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Table 1. Descriptive Statistics for the Analytic Sample of Missouri High School Seniors.

| | Mean | Standard Deviation |
|---|---|---|
| Asian | 0.02 | 0.15 |
| Black | 0.16 | 0.36 |
| Hispanic | 0.06 | 0.24 |
| White | 0.73 | 0.45 |
| Other | 0.04 | 0.18 |
| Female | 0.49 | 0.50 |
| FRL (Poverty Status) | 0.41 | 0.49 |
| IEP (Disability) | 0.12 | 0.33 |
| Standardized test score | 0.02 | 0.13 |
| Two Year College | 0.21 | 0.40 |
| Four Year College | 0.29 | 0.45 |
| No College | 0.50 | 0.50 |
| | | |
| Observations | 68302 | |

Notes: Test scores are standardized using the universe of test-takers in the sixth-grade year for the analytic cohort. The slightly positive average test score, and standard deviation below 1.0, occur because students who leave the sample between the $6^{th}$ and $12^{th}$ grades are negatively selected and have scores concentrated in the lower half of the score distribution. College-going is assessed based on enrollment in the fall immediately after high-school graduation (fall-2019 for our cohort of seniors).

Table 2. Descriptive Overview of Program Completions.

| | Share of All MO High School Seniors | Average Test Score | 2-year college | 4-year college |
|---|---|---|---|---|
| Any AP-IB Course | 0.19 | 0.65 | 0.19 | 0.63 |
| AP | 0.18 | 0.65 | 0.19 | 0.63 |
| IB | 0.01 | 0.75 | 0.18 | 0.67 |
| Any DC-DE Course | 0.31 | 0.41 | 0.27 | 0.48 |
| DC | 0.27 | 0.44 | 0.27 | 0.51 |
| DE | 0.04 | 0.34 | 0.31 | 0.38 |
| Any IRC | 0.09 | 0.10 | 0.27 | 0.26 |
| | | | | |
| IRC Field Heterogeneity | Share of All MO IRC completers | | | |
| Agriculture | 0.29 | 0.15 | 0.28 | 0.28 |
| Health Science | 0.17 | 0.03 | 0.37 | 0.28 |
| Transportation & Logistics | 0.10 | -0.17 | 0.13 | 0.07 |
| Biz Mgmt & Administration | 0.07 | 0.61 | 0.23 | 0.51 |
| Education | 0.07 | 0.04 | 0.39 | 0.32 |
| Hospitality & Tourism | 0.06 | -0.04 | 0.25 | 0.27 |
| IT | 0.06 | 0.37 | 0.23 | 0.32 |
| Manufacturing | 0.06 | -0.21 | 0.13 | 0.05 |
| Human Services | 0.05 | 0.10 | 0.34 | 0.21 |
| Architecture & Construction | 0.03 | -0.19 | 0.13 | 0.06 |
| Arts, AV & Communication | 0.03 | 0.30 | 0.30 | 0.37 |
| Law & Public Safety | 0.02 | 0.08 | 0.26 | 0.25 |

Notes: The completion shares for individual IRCs in the second horizontal panel are conditional on completing an IRC and sum to 1.0. As indicated in the text, DC and DE courses differ in that DC courses are offered at a high school by either a college-credit certified teacher or instructional television, and DE courses are offered on a college campus or at a local career center.

Table 3. Prevalence of the Largest Missouri IRCs in Other States.

| | Missouri Credential Name | Number of Other States |
|---|---|---|
| 1 | Missouri Agriculture Skill & Knowledge Assessment | 0 |
| 2 | Certified Nursing Assistant | 18 |
| 3 | Automotive Service Excellence Certification | 19 |
| 4 | AAFCS Pre-PAC - Early Childhood Education | 0 |
| 5 | ProStart National Certificate of Achievement | 8 |
| 6 | AWS Certified Welder | 5 |
| 7 | ASK Assessment of Skills and Knowledge for Business | 0 |
| 8 | AAFCS Pre-PAC - Nutrition | 0 |
| 9 | TestOut PC Pro Certification | 1 |
| 10 | ASK Fundamental Marketing Concepts | 0 |

Notes: The "Number of Other States" column displays the number of states, other than Missouri, in which the IRC indicated by the row is one of the 10 most prevalent IRCs.

Table 4. Comparative Regressions of Program Completion Patterns by Various Student Characteristics.

| | | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|
| AP-IB | Asian | 0.21 (0.03)* | | | | 0.22 (0.04)* |
| | Black | -0.05 (0.01)* | | | | 0.09 (0.01)* |
| | Hispanic | 0.00 (0.01) | | | | 0.10 (0.02)* |
| | Other Race | 0.00 (0.01) | | | | 0.04 (0.01)* |
| | Female | | 0.06 (0.01)* | | | 0.04 (0.00)* |
| | FRL | | | -0.11 (0.01)* | | -0.08 (0.01)* |
| | IEP | | | -0.18 (0.01)* | | 0.01 (0.01) |
| | ELL | | | -0.11 (0.01)* | | -0.01 (0.02) |
| | 6th-grade test score | | | | 0.14 (0.01)* | 0.14 (0.01)* |
| | | | | | | |
| DC-DE | Asian | -0.03 (.03) | | | | -0.05 (.03) |
| | Black | -0.18 (.02)* | | | | -0.06 (.03)* |
| | Hispanic | -0.07 (.02)* | | | | 0.00 (.02) |
| | Other Race | -0.06 (.01)* | | | | -0.03 (.01)* |
| | Female | | 0.10 (.01)* | | | -0.08 (.01)* |
| | FRL | | | -0.15 (.02)* | | -0.09 (.01)* |
| | IEP | | | -0.23 (.01)* | | -0.06 (.01)* |
| | ELL | | | -0.14 (.02)* | | -0.03 (.02) |
| | 6th-grade test score | | | | .14 (.01)* | 0.11 (.01)* |
| | | | | | | |
| IRC | Asian | -0.06 (.01)* | | | | -0.06 (.01)* |
| | Black | -0.06 (.01)* | | | | -0.06 (.01)* |
| | Hispanic | -0.03 (.01)* | | | | -0.03 (.01)* |
| | Other Race | -0.03 (.01)* | | | | -0.03 (.01)* |
| | Female | | 0.00 (.00) | | | 0.00 (.00) |
| | FRL | | | -0.01 (.01) | | 0.00 (.00) |
| | IEP | | | -0.04 (.00)* | | -0.03 (.01)* |
| | ELL | | | -0.04 (.01)* | | -0.01 (.01) |
| | 6th-grade test score | | | | 0.01 (.00)* | -0.00 (.00) |

Notes: The estimates in each column are from equation (1), with variables included as indicated by reported coefficients. The last column of the table reports results from the full specification shown in the text. School-clustered standard errors are in parenthesis and an * denotes the coefficient is significant at the 5 percent level.

Table 5. Comparative Analysis of Program Completion Patterns by Various Student Characteristics, Within Schools.

| | | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|
| AP-IB | Asian | 0.12 (.02)* | | | | 0.15 (.02)* |
| | Black | -0.11 (.01)* | | | | -0.03 (.01)* |
| | Hispanic | -0.04 (.01)* | | | | 0.03 (.01)* |
| | Other Race | 0.04 (.01)* | | | | -0.01 (.01) |
| | Female | | 0.06 (.00)* | | | 0.04 (.00)* |
| | FRL | | | -0.09 (.01)* | | -0.05 (.00)* |
| | IEP | | | -0.18 (.01)* | | 0.00 (.01) |
| | ELL | | | -0.16 (.01)* | | -0.04 (.02) |
| | 6th-grade test score | | | | 0.14 (.01)* | 0.13 (.01)* |
| | | | | | | |
| DC-DE | Asian | 0.02 (.01) | | | | 0.01 (.02) |
| | Black | -0.11 (.01)* | | | | -0.01 (.03) |
| | Hispanic | -0.06 (.01)* | | | | 0.01 (.01) |
| | Other Race | -0.06 (.01)* | | | | -0.03 (.01)* |
| | Female | | 0.10 (.01)* | | | 0.08 (.01)* |
| | FRL | | | -0.14 (.01)* | | -0.11 (.01)* |
| | IEP | | | -0.22 (.01)* | | -0.04 (.01)* |
| | ELL | | | -0.11 (.02)* | | -0.02 (.02) |
| | 6th-grade test score | | | | 0.14 (.01)* | 0.12 (.01)* |
| | | | | | | |
| IRC | Asian | -0.02 (.01)* | | | | -0.02 (.01) |
| | Black | -0.03 (.00)* | | | | -0.02 (.01)* |
| | Hispanic | -0.03 (.01)* | | | | -0.03 (.01)* |
| | Other Race | -0.02 (.01)* | | | | -0.02 (.01)* |
| | Female | | 0.00 (.00) | | | 0.00 (.00) |
| | FRL | | | -0.02 (.00)* | | -0.02 (.00)* |
| | IEP | | | -0.03 (.00)* | | -0.02 (.00)* |
| | ELL | | | -0.04 (.01)* | | -0.02 (.01) |
| | 6th-grade test score | | | | 0.01 (.00)* | -0.00 (.00) |

Notes: The estimates in each column are from equation (2), with variables included as indicated by reported coefficients. The last column of the table reports results from the full specification shown in the text. School-clustered standard errors are in parenthesis and an * denotes the coefficient is significant at the 5 percent level.

Table 6. Comparative Analysis of IRC Cluster Patterns by Various Student Characteristics, Conditional on Any IRC Completion.

| | | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|
| Relative Risk of Cluster 1 Relative to Cluster 3 | Asian | 1.98 | | | | 1.81 |
| | Black | 1.15 | | | | 1.58* |
| | Hispanic | 0.68 | | | | 0.99 |
| | Other Race | 1.06 | | | | 1.01 |
| | Female | | 7.16* | | | 6.94* |
| | FRL | | | 0.51* | | 0.58* |
| | IEP | | | 0.26* | | 0.89 |
| | ELL | | | 0.28 | | 0.93 |
| | $6^{th}$-grade test score | | | | 3.89* | 3.52* |
| | | | | | | |
| Relative Risk of Cluster 2 Relative to Cluster 3 | Asian | 0.88 | | | | 0.61 |
| | Black | 1.06 | | | | 0.71* |
| | Hispanic | 0.88 | | | | 0.85 |
| | Other Race | 1.56* | | | | 1.2 |
| | Female | | 17.06* | | | 16.87* |
| | FRL | | | 0.84* | | 0.77* |
| | IEP | | | 0.35* | | 0.69* |
| | ELL | | | 0.75 | | 1.22 |
| | $6^{th}$-grade test score | | | | 1.66* | 1.46* |

Notes: Each cell reports a relative risk ratio for the focal cluster relative to Cluster 3, which is the baseline cluster and contains IRCs that generally serve students with low test scores and who are unlikely to go to college. The sample includes only individuals who complete an IRC. Statistical significance is assessed using the underlying output from the multinomial logistic regression corresponding to each reported relative risk ratio. An * denotes that the relative risk ratio is statistically different from 1.0 at the 5 percent level or better, where a value of 1.0 indicates no differential selection along the dimension considered between the focal cluster (i.e., Cluster 1 or 2) and the baseline cluster (i.e., Cluster 3).

Appendix A
Supplementary Tables

Appendix Table A1. IRC Cluster Assignments for Individual IRCs in Missouri.

| IRC Code | Category | Completers (Count) | Average Map | Cluster |
|---|---|---|---|---|
| ACP | Architecture & Construction | 6 | * | 1 |
| ADDA | Architecture & Construction | 2 | * | 1 |
| ADOBE-CAC | Arts, AV & Communication | 113 | 0.4 | 1 |
| ASK | Biz Mgmt & Administration | 195 | 0.42 | 1 |
| ASK-FIN | Biz Mgmt & Administration | 45 | 0.72 | 1 |
| ASK-MKTG | Biz Mgmt & Administration | 199 | 0.77 | 1 |
| AAFCS-N | Health Science | 106 | 0.54 | 1 |
| CCNA-S | Health Science | 3 | * | 1 |
| AAFCS-FAM | Human Services | 119 | 0.29 | 1 |
| AAFCS-FASH | Human Services | 34 | 0.37 | 1 |
| AAFCS-ID | Human Services | 4 | * | 1 |
| CAP | IT | 3 | * | 1 |
| CCENT | IT | 32 | 0.66 | 1 |
| COMPNTIA | IT | 4 | * | 1 |
| ETA | IT | 10 | * | 1 |
| MOS | IT | 33 | 0.4 | 1 |
| MTA | IT | 67 | 0.55 | 1 |
| TONETWPRO | IT | 35 | 0.31 | 1 |
| TOSECPRO | IT | 4 | * | 1 |
| ISCET | Manufacturing | 6 | * | 1 |
| MT1 | Manufacturing | 12 | * | 1 |
| AGSK | Agriculture | 1703 | 0.15 | 2 |
| AGVET | Agriculture | 23 | * | 2 |
| GCOM-SUSA | Arts, AV & Communication | 45 | 0.04 | 2 |
| AAFCS-ECE | Education | 254 | 0.02 | 2 |
| AAFCS-EF | Education | 148 | 0.09 | 2 |
| YDEVA | Education | 7 | * | 2 |
| CNA | Health Science | 911 | -0.03 | 2 |
| MABDAS | Health Science | 6 | * | 2 |
| AAFCS-CA | Hospitality & Tourism | 161 | -0.01 | 2 |
| AHLA | Hospitality & Tourism | 5 | * | 2 |
| PROSTART | Hospitality & Tourism | 176 | -0.06 | 2 |
| AAFCS-FS | Human Services | 29 | * | 2 |
| CDEVA | Human Services | 46 | -0.19 | 2 |
| CSC | IT | 8 | * | 2 |
| TOPCPRO | IT | 132 | 0.26 | 2 |
| FIREII | Law & Public Safety | 14 | * | 2 |
| MOLESK | Law & Public Safety | 56 | 0.12 | 2 |
| NREMT | Law & Public Safety | 27 | * | 2 |
| CCC | Architecture & Construction | 22 | * | 3 |
| HVAC | Architecture & Construction | 35 | -0.25 | 3 |
| NCCER-CARP | Architecture & Construction | 11 | * | 3 |
| NCCER-CNST | Architecture & Construction | 19 | * | 3 |
| NCCER-MAS | Architecture & Construction | 2 | * | 3 |
| PACT | Architecture & Construction | 111 | -0.14 | 3 |
| ACF | Hospitality & Tourism | 39 | -0.1 | 3 |
| AAFCS-HOUS | Human Services | 8 | * | 3 |

| | | | | |
|---|---|---|---|---|
| CSCBE | Human Services | 26 | * | 3 |
| NTSCBE | Human Services | 12 | * | 3 |
| COMPSTRTIA | IT | 8 | * | 3 |
| COMPTIA | IT | 5 | * | 3 |
| AWS | Manufacturing | 263 | -0.26 | 3 |
| NIMS | Manufacturing | 50 | -0.13 | 3 |
| ASE | Transportation & Logistics | 495 | -0.15 | 3 |
| ICAR | Transportation & Logistics | 79 | -0.23 | 3 |
| NATEF | Transportation & Logistics | 8 | * | 3 |

Notes: Average MAP scores are censored for cells with fewer than 30 students. IRC ordering within clusters is alphabetical by category and within category, by IRC code.

Appendix Table A2. Descriptive Statistics for IRC Clusters.

| Cluster No. | Share Any College | Share Two-Year College | Share Four-Year College | Average Standardized Test Score | Female Share | No. of IRC Completers |
|---|---|---|---|---|---|---|
| Cluster 1 | 0.69 | 0.23 | 0.46 | 0.54 | 0.43 | 907 |
| Cluster 2 | 0.59 | 0.32 | 0.27 | 0.08 | 0.65 | 3876 |
| Cluster 3 | 0.20 | 0.14 | 0.06 | -0.19 | 0.10 | 1193 |

Appendix Table A3. Seemingly Unrelated Regression Results (Analogous to Table 4).

| | | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|---|
| AP-IB | Asian | 0.21 (.01)* | | | | 0.22 (.01)* |
| | Black | -0.05 (.00)* | | | | 0.09 (.00)* |
| | Hispanic | 0.00 (.01) | | | | 0.10 (.01)* |
| | Other Race | 0.00 (.01) | | | | 0.04 (.01)* |
| | Female | | 0.06 (.00)* | | | 0.04 (.00)* |
| | FRL | | | -0.11 (.00)* | | -0.08 (.00)* |
| | IEP | | | -0.18 (.00)* | | 0.01 (.01) |
| | ELL | | | -0.11 (.01)* | | -0.01 (.02) |
| | 6th-grade test score | | | | 0.14 (.00)* | 0.14 (.00)* |
| | | | | | | |
| DC-DE | Asian | -0.03 (.01) | | | | -0.05 (.01)* |
| | Black | -0.18 (.00)* | | | | -0.06 (.01)* |
| | Hispanic | -0.07 (.01)* | | | | 0.00 (.01) |
| | Other Race | -0.06 (.01)* | | | | -0.03 (.01)* |
| | Female | | .10 (.00)* | | | 0.08 (.00)* |
| | FRL | | | -0.15 (.00)* | | -0.09 (.00)* |
| | IEP | | | -0.21 (.01)* | | -0.06 (.01)* |
| | ELL | | | -0.14 (.01)* | | -0.03 (.02) |
| | 6th-grade test score | | | | 0.14 (.00)* | 0.11 (.00)* |
| | | | | | | |
| IRC | Asian | -0.06 (.01)* | | | | -0.06 (.01)* |
| | Black | -0.06 (.00)* | | | | -0.06 (.00)* |
| | Hispanic | -0.03 (.00)* | | | | -0.03 (.01)* |
| | Other Race | -0.03 (.01)* | | | | -0.03 (.01)* |
| | Female | | 0.00 (.00) | | | 0.00 (.00) |
| | FRL | | | -0.01 (.00)* | | 0.00 (.00) |
| | IEP | | | -0.04 (.00)* | | -0.03 (.00)* |
| | ELL | | | -0.04 (.01)* | | -0.01 (.01) |
| | 6th-grade test score | | | | 0.01 (.00)* | -0.00 (.00)* |

Notes: These results are from regressions that match the regressions used to produce Table 4, but within the SUR framework to allow for correlated errors within students across equations for the different programs. The errors are not clustered by school. The last column of the table reports results from the full specification shown in the text. An * denotes the coefficient is significant at the 5 percent level.