



Cheapskin Effects? The Heterogeneous Value of Industry-Recognized Certificates Earned by High School Students

Tasneem Sultana

The University of Texas at Austin

Madison E. Andrews

The University of Texas at Austin

Matt S. Giani

The University of Texas at Austin

Human capital theory and signaling models posit that educational credentials convey information about workers' skills, producing discrete labor market returns beyond years of schooling. While extensive evidence documents these "sheepskin effects" for degrees, far less is known about industry-recognized certifications (IRCs) earned in high school. Using statewide administrative data from Texas, this study examines the relationship between IRC attainment and early labor market outcomes for six cohorts of high school graduates ($n = 1,698,846$). Employing correlated random effects models, we estimate associations between IRC receipt and employment, earnings, and job stability and assess heterogeneity by subject area and demographics. On average, IRC attainment is unrelated to employment but associated with a 9 percent increase in earnings, larger than returns from each CTE course, but smaller than returns from CTE concentration. However, these benefits depend critically on alignment to CTE coursework. IRCs earned in the same career field as a student's CTE concentration are associated with substantial gains in employment, earnings, and job stability, whereas misaligned IRCs not only confer no earnings benefits, but also are associated with losses in employment and job stability. Returns also vary significantly across credential fields and demographic groups, with larger earnings gains for White, male, and non-low-income students. These findings suggest that IRCs produce sheepskin effects only under specific conditions and raise concerns that IRCs are conducive to labor market inequity.

VERSION: February 2026

Suggested citation: Sultana, Tasneem, Madison E. Andrews, and Matt S. Giani. (2026). Cheapskin Effects? The Heterogeneous Value of Industry-Recognized Certificates Earned by High School Students. (EdWorkingPaper: 26-1412). Retrieved from Annenberg Institute at Brown University: <https://doi.org/10.26300/evgq-re17>

Cheapskin Effects? The Heterogeneous Value of Industry-Recognized Certificates Earned by High School Students

Tasneem Sultana, Madison E. Andrews, and Matt Giani

The University of Texas at Austin

Author's Note: This research was supported by the Bill and Melinda Gates Foundation (INV#:060866) and the National Institute for Child Health and Human Development (P2CHD042849 and T32HD007081). The conclusions of this research do not necessarily reflect the opinion or official position of the Texas Education Research Center, the Texas Education Agency, the Texas Higher Education Coordinating Board, the Texas Workforce Commission, or the State of Texas. Correspondence can be directed to Matt Giani, Research Associate Professor, Department of Sociology, the University of Texas at Austin, matt.giani@austin.utexas.edu.

Abstract

Human capital theory and signaling models posit that educational credentials convey information about workers' skills, producing discrete labor market returns beyond years of schooling. While extensive evidence documents these "sheepskin effects" for degrees, far less is known about industry-recognized certifications (IRCs) earned in high school. Using statewide administrative data from Texas, this study examines the relationship between IRC attainment and early labor market outcomes for six cohorts of high school graduates ($n = 1,698,846$). Employing correlated random effects models, we estimate associations between IRC receipt and employment, earnings, and job stability and assess heterogeneity by subject area and demographics.

On average, IRC attainment is unrelated to employment but associated with a 9 percent increase in earnings, larger than returns from each CTE course, but smaller than returns from CTE concentration. However, these benefits depend critically on alignment to CTE coursework. IRCs earned in the same career field as a student's CTE concentration are associated with substantial gains in employment, earnings, and job stability, whereas misaligned IRCs not only confer no earnings benefits, but also are associated with losses in employment and job stability. Returns also vary significantly across credential fields and demographic groups, with larger earnings gains for White, male, and non-low-income students. These findings suggest that IRCs produce sheepskin effects only under specific conditions and raise concerns that IRCs are conducive to labor market inequity.

Keywords: Career and Technical Education (CTE), Industry-Recognized Certifications (IRCs), Labor Market Outcomes, Sheepskin Effects, Credentialing Effects

1. Introduction

Human capital theory posits that education provides students and workers with knowledge and skills that have economic value and can be exchanged for better pay and employment prospects in the labor market (Becker 1962, 1975). However, it may be difficult for employers to observe prospective workers' human capital. Educational credentials provide signals to employers that job candidates possess the skills they seek. And while there is a breadth of evidence supporting labor market returns for additional years in school (e.g., Mincer 1974; Psacharopoulos and Patrinos 2018), research shows distinct jumps in labor market outcomes when individuals earn formal credentials such as high school diplomas or college degrees (Hungerford and Solon 1987; Spence 1974). This phenomenon, known as the “sheepskin effect,” highlights the added value of a credential beyond the accumulation of the knowledge and skills gained from one's educational experience.

The majority of research on the sheepskin effects of educational credentials has focused on high school diplomas and equivalents (e.g. GEDs) (Jaeger and Page 1996; Park 1999; Rodríguez and Muro 2015; Ferrer and Riddell 2001) or college degrees, including associate and bachelor's degrees (Baum 2014; Hout 2012; Pascarella and Terenzini 2005; Jaeger and Page 1996; Ferrer and Riddell 2001). Despite some exceptions (Belfield and Bailey 2017; Backes, Holzer, and Velez 2015; Layard and Psacharopoulos 1974; Clark and Martorell 2014), this research has generally found that these long-established educational credentials make a considerable difference for students' labor market outcomes.

However, the non-degree credential space has grown rapidly. Data from the US Census on educational attainment historically grouped together individuals with “some college, no degree” and those with non-degree credentials, making analysis of long-term trends in attainment

of these credentials difficult. However, more recent data from the National Center for Education Statistics shows that postsecondary institutions in the United States awarded more certificates than associate's degrees for the first time in 2021-22 (NCES, 2024). Despite the growth in these credentials, evidence suggests that their benefits for students' employment outcomes are decidedly mixed (Cunningham 2019; Carnevale, Rose, and Hanson 2012; D. Xu and Trimble 2016; Dadgar and Trimble 2015; Jepsen, Troske, and Coomes 2014)

Postsecondary institutions have historically been the primary purveyors of educational credentials. However, businesses, industry groups, and quasi-governmental regulatory bodies have long issued credentials to individuals demonstrating knowledge and skills in a particular domain, and this trend is growing (Albert 2017). As state and federal education policy has shifted from a “college-for-all” paradigm to a “college and career readiness” approach, a growing number of states have incorporated high school students' attainment of these industry-recognized certifications (IRCs) into state policy and school redesign. A recent survey conducted by Advance CTE found that 44 states have publicly available credential lists, 35 states reported funding credentials through state or federal funding, 26 states have incorporated IRC attainment in their Every Student Succeeds Act (ESSA) and/or state accountability systems, 22 states include IRCs as a Perkins indicator, and 11 states have incorporated IRCs into high school graduation requirements (Advance CTE 2025b, 2025a). In Texas, the site of the present study, the incorporation of IRCs into school accountability and funding systems has contributed to the percentage of high school graduates earning IRCs increasing from 3%-33% from 2016-17 to 2022-23.

The logic of this strategy is that IRCs may be a more reliable signal of students' abilities than a high school diploma or the curriculum a student completed, including career and technical

education (CTE) coursework presumably designed to prepare students more directly for the labor market. IRCs may also be particularly beneficial for students who do not pursue postsecondary education out of high school. However, limited research has examined the relationship between high school students' receipt of IRCs and their postsecondary outcomes. This is particularly important given the strong policy incentives for schools to award students IRCs to improve accountability ratings and receive bonus funding. Indeed, research has shown that the majority of high school students earning IRCs do not concentrate in the same CTE subject as their certification (Giani et al. 2025). This phenomenon, which has been described as *curricular-credential decoupling*, raises questions about the value of IRCs for high school graduates.

A small number of studies have examined the relationship between high school students' attainment of IRCs and their labor market outcomes (Giani 2022; Baird, Bozick, and Zaber 2022; D. Xu et al. 2024; Hendricks et al. 2021), finding evidence of short-term employment and wage gains. To our knowledge, no peer-reviewed research has used statewide administrative data on six entire cohorts of high school graduates to examine the relationship between IRC receipt and labor outcomes, investigated the extent to which alignment between IRCs students earn and the CTE courses they complete moderates this relationship, or estimated the extent to which these relationships vary across demographic groups. This is particularly important given prior research suggesting gendered and racialized patterns in the relationship between sub-baccalaureate credentials and labor outcomes (Baird, Bozick, and Zaber 2022; D. Xu et al. 2024).

This study addresses these gaps using statewide administrative data from Texas, which incorporated IRCs into high school accountability policy in 2016-17 and financially incentivized schools to award IRCs to students beginning in 2018-19. Our sample includes students who

graduated from a Texas public school between 2017 and 2022 ($n = 1,698,846$), 12% ($n = 209,007$) of whom earned an IRC before graduating. We link students with their Unemployment Insurance (UI) records to examine their post-high school employment and earnings. We then use a correlated random effects (CRE) approach, which combines the benefits of controlling for individual fixed effects that absorb time-invariant unobserved characteristics with the ability to estimate time-invariant covariates (Allison 2009; Schunck 2013; Wooldridge 2019).

We make a number of contributions to the literature. We show that, on average, IRC receipt in high school does not relate to employment probability but is associated with a roughly 9% increase in earnings and 0.2pp increased likelihood of employment stability. This wage increase is 3% larger than the benefit of each individual CTE course students complete, but smaller than the 23% boost associated with completing a CTE concentration (defined as completing three or more credits in the same CTE subject). However, the relationship between IRC receipt and earnings depends heavily on whether the IRC was earned in a CTE subject in which the student concentrated. Misaligned IRC receipt is inversely related to employment (-0.5pp) and job stability (-0.3pp) and unrelated to earnings, whereas aligned IRC receipt is positively and significantly related to earnings (14.7%), employment (1.3pp), and job stability (1.3pp). We also find substantial heterogeneity in the labor market benefits of IRCs across fields, with some IRC subjects associated with decreases in earnings of roughly 30% and others associated with increases in earnings nearly 35%. In terms of student characteristics, we find that most student groups experience employment and wage boosts from aligned IRCs, but White and male students receive greater and more consistent benefits compared to other students. Finally, we find some evidence that the relationship between IRC receipt and labor outcomes has declined over time, potentially due to the rapid growth in misaligned IRCs.

Our paper is outlined as follows. We begin by discussing IRCs in more detail, including how they have been incorporated into educational reform through federal and state policy. We then review prior literature on human capital and sheepskin effects in education, with a focus on the estimated effects of CTE coursework, non-degree credentials, and IRCs. This is followed by a description of our methods before we present our findings. In our discussion, we interpret our findings through the lens of prior literature on sheepskin effects in education, with an emphasis on the issue of IRC misalignment potentially induced by the design of federal and state policy.

1.1. Labor and Policy Context

The returns associated with credentials and additional years of schooling may be particularly relevant at a time where there is both increasing skepticism of traditional college degrees as signifiers of workforce skills and a movement towards new forms of credentialism in education and work. There are many critiques of the “college for all” paradigm (Rosenbaum 2001; Rosenbaum et al. 2015) and growing public skepticism of the value of higher education in the face of skyrocketing costs (Pew Research Center 2024). Simultaneously, there is a movement toward “skills-based hiring,” with skills often signified through non-traditional credentials such as IRCs (Fuller et al. 2022). Several large corporations such as Amazon, Google, and Microsoft have announced removing degree requirements for many of their jobs, often replacing them with certifications they have developed (Díaz et al. 2022). Credential Engine, an initiative supported by the Lumina Foundation and JP Morgan Chase, has documented over one million distinct credentials available in the US (Credential Engine, n.d.). In all, this suggests that non-traditional credentials hold an increasingly significant and valuable position in the modern labor market.

Simultaneously, there has been a surge in policy interest and research related to “college and career readiness” (CCR) for high school students (Darling-Hammond, Wilhoit, and Pittenger

2014), and particularly, CCR efforts encouraging students to earn IRCs. IRCs are credentials conferred by businesses, industry groups, or state certifying entities to individuals demonstrating competency in a particular domain. In secondary education, IRCs are typically embedded in career and technical education (CTE) programs of study. For instance, students might pursue a Certified Veterinary Assistant license in an Agriculture CTE program or an Occupational Safety and Health Administration (OSHA) certification in a Construction CTE program.

The increased prominence of IRCs is the result of several policies that explicitly link CTE and IRCs. The Every Student Succeeds Act (ESSA, 2015) placed new requirements on states to incorporate components of college and career readiness, like CTE and IRCs, into state accountability plans (Hackmann, Malin, and Bragg 2019), and by 2023, at least 16 states had begun using IRC receipt as an indicator of CCR in their ESSA plans (Education Commission of the States 2023). Perkins legislation (Perkins V, 2018) made the attainment of recognized post-secondary credentials, including IRCs, one of the core accountability indicators of student performance in secondary CTE, and at least 22 states chose this indicator.

By linking CTE to credentials explicitly valued by industry groups, IRCs are then conceived as a skill-signaling mechanism for the human capital acquired through CTE coursework. This logic parallels the sheepskin effect, positing that coursework alone may not be a strong enough signal to employers that prospective employees possess the knowledge and skills needed to perform particular job functions, compared to candidates who have completed both coursework and a credentialing process. Additionally, licenses in fields such as education, health care, and human services may be required before one can be employed as a childcare provider, certified nurse assistant, or cosmetologist. IRCs may therefore serve as skill-signaling or formal screening mechanisms, depending on the IRC and the occupation.

1.2. Benefits of CTE & IRCs

Research shows that CTE participation has been linked to several education and workforce outcomes, including an increased likelihood of high school graduation (Dougherty 2018; Brunner, Dougherty, and Ross 2023; Lindsay et al. 2024), college enrollment (Brunner, Dougherty, and Ross 2023), short-term employment (Lindsay et al. 2024) and short-term wage returns (Hendricks et al. 2021; Kreisman and Stange 2020; Brunner, Dougherty, and Ross 2023). However, there remains a lack of rigorous evidence suggesting that CTE participation improves long-term earnings (Lindsay et al., 2024). Further, initial labor market benefits may fade over time, particularly if CTE students are unable to enter careers with opportunities for advancement or to upskill, or perhaps upskill-signal, over time (Hanushek et al. 2017).

Like participating in CTE coursework, early research suggests that earning an IRC in high school is associated with an increased likelihood of high school graduation (Walsh et al. 2019; Glennie, Lauff, and Ottem 2017), college enrollment and graduation (Glennie et al. 2023; Glennie, Ottem, and Lauff 2020), short-term employment (Giani 2022; Baird, Bozick, and Zaber 2022; D. Xu et al. 2024) and short-term wage returns (Giani 2022; Baird, Bozick, and Zaber 2022; D. Xu et al. 2024; Hendricks et al. 2021). However, IRC participation varies across gender, race, student achievement levels (Giani 2022; Walsh et al. 2019; Eagan and Koedel 2021; Glennie, Lauff, and Ottem 2017), and the relationships between IRC receipt and postsecondary and workforce outcomes vary across IRC subject area (D. Xu et al. 2024; Giani 2022).

For instance, D. Xu et al. (2024) found positive relationships between IRC receipt and both employment probability and wages, and analyzed variation in these outcomes across career fields, but this study sampled community college students enrolled in a specific noncredit

workforce training program in Virginia, which they acknowledge enrolls a specific-subset of the state's population. Similarly, Baird and colleagues (2022) documented employment and wages gains associated with IRCs, which varied by gender and level of education, but their analyses were not specific to high school graduates or credentials. A report from the Fordham Institute documented similar short-term gains and variation in outcomes across CTE fields for high school graduates (Giani 2022), but this report only examined three cohorts of graduates and did not investigate the relationship between IRC alignment and outcomes. Further, research suggests not only that there is a limited relationship between IRC receipt and labor-market needs (Dalton et al. 2021), meaning students may not be earning credentials that actually provide entry points into in-demand fields, but also that the majority of IRC earners were neither enrolled in a major nor employed in an industry after high school that matched their IRCs (Giani 2022, 12), further calling into question the true value of these credentials.

Skill-signals like IRCs are contextual, and just as there may be heterogeneity in the returns to schooling and the benefits of college completion by the field of education and employment, there may exist heterogeneity in *who* benefits the most from *which* IRCs. For instance, an IRC could be a positive signal for certain job opportunities or career fields, and a negative signal for others. Students can earn IRCs outside of, or “misaligned” to, the career field of their CTE courses; misaligned IRCs may hold less economic value for students, or more generally, IRCs may hold little value if students pursue opportunities outside of that career field. Further, IRCs are being rapidly adopted, and their economic value may decrease as the relative supply and demand of workers with those skills or signals increases. At the individual level, students from historically marginalized backgrounds might experience the most precarity in the labor market and therefore could benefit the most from a signaling boost associated with IRC

attainment. Conversely, IRCs may be insufficient to counteract labor market disadvantages, or could even exacerbate inequity if there are stratified returns or participation patterns.

In summary, whether IRCs provide value, if that value surpasses the value of CTE coursework, and how these patterns vary across discipline, CTE-IRC alignment, and student demographics have been insufficiently explored. In this paper, we investigate:

1. How does IRC attainment relate to students' postsecondary labor market (LM) outcomes, specifically employment, wages, and employment stability?
2. How does the relationship between IRC attainment and LM outcomes vary across academic characteristics, like career cluster, CTE-IRC alignment, and specific IRCs?
3. How does the relationship between IRC attainment and LM outcomes vary across students' demographic characteristics?

2. Methods

2.1. Data

We use longitudinal data housed in the Texas Education Research Center (TERC), containing K-12 records from Texas Education Agency (TEA), postsecondary data from the Texas Higher Education Coordinating Board (THECB), and labor market information from the Texas Workforce Commission (TWC). This state clearinghouse data allows identifying the IRCs students earn at high school (HS) along with HS course-taking, demographics, college enrollment and course-taking, and labor market outcomes. We use data for the high school graduates between 2017-2022 and follow them into the postsecondary institutions and the labor market until the fourth fiscal quarter of 2023. For labor market outcomes, we collapse quarterly records so that we observe one employment record per quarter, per student. For example, if a

student worked three jobs in a quarter and earned \$1,000 in each job, we would aggregate those records so that the student would have one employment record earning \$3,000 in that quarter. In the next subsections, we describe the variables and econometric model used in our analysis.

2.2. Sample Characteristics

Our analytic sample consists of Texas public HS graduates between 2017-2022, observed in the labor market over the fiscal quarters (FQs) after HS graduation until the fourth quarter of 2023. Thereby, we have an unbalanced panel of 1,475,015 students. We observe the oldest cohort for 26 consecutive quarters starting from 2017 quarter 3 and the youngest cohort for six quarters. Our student-by-quarter level sample consists of almost 19 million observations ($N = 18,860,879$). Table 1 describes sample sizes, means, and standard deviations to give a sense of the sample composition. In terms of race/ethnicity, 49% of our sample identifies as Hispanic/Latino, 31% are non-Hispanic White, 13% are Black, 4% are Asian, and the remaining 3% are multiracial and all other races/ethnicities. Roughly half of our sample is female (51%), while 67% is economically disadvantaged. The average student in our sample graduates with 4.7 CTE credits. Twelve percent of the sample earned an IRC before graduating, although only about one-third of IRC recipients earned an IRC and concentrated in the same CTE field (i.e. an Aligned IRC). Among the twelve IRC clusters, Business, Marketing, and Finance IRCs are the most common (4% of full sample) followed by Health, Agriculture, and Manufacturing (2%) IRCs. On the contrary, Education and IT IRCs are the least common, followed by Arts, Human Services, and Transportation IRCs, all below 1%.

[Table 1]

In table 2, we descriptively analyze if the demographic composition and labor market outcomes vary across those with and without an IRC, and across those with an aligned and misaligned IRC. A greater percentage of all Black students, and a lower percentage of all Hispanic students, have no IRCs. Students earning an IRC accumulate 1.6 more CTE credits; non-CTE credits are not noticeably different. Descriptives reveal employment and log wages are slightly higher for IRC recipients. Looking into columns (3) and (4), more white students earn a misaligned IRC than an aligned IRC, and more male and female students earn a misaligned IRC than an aligned IRC. Employment differences are less pronounced, but the log wage for those with misaligned IRCs is slightly higher than for those with aligned IRCs.

[Table 2]

2.3. Dependent Variable

To understand quarterly labor market outcomes after HS graduation, we employ three primary outcomes - employment, log wages, and employment stability over the quarters. We start by identifying all the HS graduates in postsecondary labor market in the Employment-wage records from the TWC and creating a student-by-quarter record such that an individual's earnings across all jobs held are summed into one observation.

We define employment dichotomously as an individual having a non-missing, non-zero wage record in a given quarter (=1) or not (=0). For the wage analysis, the outcome is the total wages across all employment records in a quarter. We convert all quarterly wages to 2019 price levels to adjust for inflation (Minneapolis FED, n.d.). Then we log transform all wages, assigning a non-zero small wage to those unemployed so that their log wages approximate zero. This approach assumes individuals with missing employment records earned zero wages in those

quarters. This assumption is wrong to some extent – individuals with missing wage records may be self-employed or working outside of Texas, which could bias our results. We discuss these limitations and robustness checks used to examine how violations of this assumption may have biased our results below. Finally, we define employment stability for an individual from one quarter to the next as remaining employed between the two periods.

2.4. Independent Variable

Our primary variables of interest relate to IRCs students earned in high school. We use three measures to examine the overall association between IRC receipt and postsecondary outcomes. Our simplest measure is a dichotomous indicator that denotes if a student has earned any IRC – meaning it allows us to capture the overall association between IRC attainment and labor market outcomes. Roughly 12% of the sample earned an IRC in high school. Our second measure is motivated by the growing concern over CTE-IRC misalignment (Giani et al. 2025). Thereby, we use a categorical variable that classifies students in three groups – those with no IRC, those with IRCs aligned with their CTE concentration cluster, and those with IRCs misaligned with CTE concentration. As shown in Table 1, only 33% of all IRCs earned by students in our sample were classified as aligned. Finally, we create a continuous variable that counts the number of IRCs students earned in high school to estimate the incremental association between each additional IRC and students’ postsecondary outcomes.

In the next step, we further disaggregate IRCs by their subjects or clusters and employ an indicator for each cluster. Following TEA (2024), we categorize IRCs into twelve career clusters: Agriculture; Architecture and Construction; Arts, Audio, and Visuals; Business, Marketing, and Finance (BMF); Education; Health Sciences; Hospitality; Human Services; Information Technology; Manufacturing; Public Service; and Transportation. Using these cluster indicators

reveals insights into which IRC clusters are rewarded in the labor market and which ones are not as beneficial.

2.5. Control Variables

Students' IRC attainment and postsecondary labor market outcomes could be associated with a host of factors including demographic characteristics, courses completed in high school, highest postsecondary credential, and the opportunity cost of labor market participation in terms of college credits attempted per FQ. We control for these variables to isolate the relationship between IRC attainment, employment, and log wages and to estimate whether IRCs provide an economic advantage above the underlying human capital gained from CTE coursework.

First, we control for students' HS course-taking, specifically differentiating all credits earned in CTE courses and those earned in non-CTE courses, since CTE courses could be more strongly associated with employment outcomes. Additionally, we control for CTE concentration (i.e., completes three or more courses in the same career cluster) to identify potential sheepskin effects of completing a CTE program of study. We also control for HS graduation year, assuming each cohort could be subject to a different set of IRC offerings at HS coupled with differing labor market conditions, suggesting returns to IRC could vary by year.

Next, our demographic controls consist of students' race/ethnicity, age, gender, low-income status, special education status, gifted status, and English as a second language (ESL) status in HS. We treat all these factors as time invariant except for the age variable at each FQ. We classify race/ethnicity following the US Census guidelines that first categorize individuals as either of Hispanic or Latino, or not. Then the non-Hispanic/Latino individuals are classified into Asian, Black/African American, Non-Hispanic White, and other races (Native

Hawaiian or Pacific Islander, Multiracial, or other than those mentioned). In all our statistical models, we designated Hispanic as the base racial category since that is the largest subpopulation in our sample. Age is represented using a continuous variable. For gender, we follow the US Census classification and use a female indicator variable to denote the student's gender.

Our measure of low-income status is informed by the TEA indicator that defines low-income as students eligible for the Free or Reduced-Price Lunch Program (FRL), Aid to Families with Dependent Children (AFDC), or other comparable federal programs. Similarly, our indicators for special education and gifted education are guided by the federal definition, referring to students with disabilities and students performing at a higher ability than their age, respectively. Finally, we control for students' ESL status using a categorical variable that indicates if a student participates in ESL program or not (reference category in statistical models), and what type of program participants are enrolled in (i.e., content based or integrated as opposed to pull-out or separate instruction).

Our final set of controls encompasses a student's postsecondary credit enrollment and the highest credential held at each FQ, since the former could reduce time available for labor market participation while the latter could improve employment opportunities. We introduce credit hours attempted using a continuous variable that sums all the credits a student enrolls for in college in a FQ. The highest credential variable is a time-variant measure of postsecondary educational attainment. We use a categorical variable that indicates one of the following highest credentials that a student holds – HS diploma, Level 0 Certifications (certifications below 15 credits), Level 1 Certifications (requiring less than a year), Level 2 Certifications (requiring 1-2 years), Technical/Applied Associate, Academic Associate, Technical Bachelor's, Academic Bachelor's, Graduate level certification, Professional Doctoral, and Research Doctoral. In the presence of

individual fixed effects as described in the next section and this set of controls, we isolate the association between IRC attainment and postsecondary labor market outcomes. We present variable information along with key summary statistics in Table 1.

2.6. Econometric Model

We employ a Correlated Random Effects (CRE) model to identify the association between IRC attainment and labor market outcomes, as follows:

$$(1) Y_{it} = \beta_0 + \beta_1 IRC_i + \beta_2 X_{it} + \beta_3 Z_i + \beta_4 \bar{X}_i + \lambda_t + \alpha_i + \varepsilon_{it}$$

Here, Y_{it} denotes the outcome (i.e., employment, log wages, or stability) for student i in FQ t . IRC_i is our measure of IRC attainment, meaning β_1 captures the labor market effect of IRC. X_{it} is a vector of time varying controls – age, highest credential attained, and college credits attempted. Z_i is a vector of time invariant controls – race, gender, low-income status, gifted status, special education status, ESL participation, and CTE and non-CTE credits attained in high school. \bar{X}_i is the student level mean of time-invariant factors. λ_t and α_i represent FQ and student fixed effects, respectively. ε_{it} represents the error term, which is clustered at the student level.

We begin with a model where the IRC_i variable is a dichotomous indicator of whether students received any IRC or not (RQ #1). To explore whether the relationship between IRC receipt and labor outcomes depends upon the characteristics of IRCs, such as whether they were earned in an aligned field, their subject, the number of IRCs students earned, or the specific IRC students earned, we replace the dichotomous indicator of IRC receipt with different parameterizations in subsequent models (RQ #2). To explore heterogeneous effects of IRC

receipt across demographic groups (RQ #3), we fit model (1) to various subgroups of students based on their race/ethnicity, gender, and economic status.

Our employment definition and log transformation of wages allows us to include the unemployed quarters in the analysis even though employment-wage records do not record out-of-state employment records causing those records seeming like unemployed even if they might not be. Since excluding them from the analysis as quarters unemployed could potentially bias our estimates, we retain these records by changing the wages only trivially to get the estimates for the full sample. We also ran alternative analyses that condition wages on employment, meaning we only observe log wages for employed student-quarters, and our results are roughly similar regardless of the approach we take to dealing with missing wage records.

3. Findings

3.1. The Relationship between IRC Receipt and Labor Outcomes

Table 3 presents our results estimating the relationship between IRC receipt and students' postsecondary labor outcomes of employment, log-wages, and employment stability. Three different models are fit to each outcome, each with a different parameterization of the IRC variable. The first includes the dichotomous indicator of any IRC receipt, the second disaggregates IRCs into aligned and misaligned credentials, and the third includes a continuous variable counting the number of IRCs students earned. Table 3 presents only the estimates for the key IRC variables and the sheepskin controls measuring students' completion of overall high school credits, CTE credits, and CTE concentrator status. The full model results are included in the online supplementary materials.

Our first set of estimates suggests IRC receipt is not meaningfully associated with quarterly employment, whereas additional CTE credits and attaining a CTE concentrator status are associated with 0.7 percentage points (pp) and 0.3pp, respectively. Students attaining an IRC earn 8.7% greater wages on average; this earnings estimate is larger than the estimate for the relationship between each CTE credit students earned (5.5%), but smaller than attaining CTE concentrator status (22.8%) on earnings. Finally, students who earn an IRC are 0.2pp more likely to experience job stability than those without an IRC, which is smaller than the boost from additional CTE credits (.7pp) and concentration (.5pp).

Earning an aligned IRC increases quarterly employment probability by 1.3 pp, wages by 14.7%, and job stability probability by 1.3pp, on average. On the contrary, earning a misaligned IRC reduces employment probability by 0.5pp and job stability by 0.3pp, and we find no significant relationship between misaligned IRC receipt and earnings. The model with the continuous IRC count measure suggests each additional IRC increases wages by 3.2%, and job stability by 0.2pp.

[Table 3]

3.2. How IRC Estimates Vary Across Subject and Specific Certifications

To further examine variation in the relationship between IRCs and labor outcomes, the results in Table 4 replace the broad IRC variables with a categorical variable representing the subject of the IRC students earned. This analysis shows variation by IRC subject area. IRCs in six career clusters increase employment probability: Agriculture (0.6pp), Construction (2.5pp), Education (2.8pp), Health (0.4pp), Hospitality (1.9pp), and Transportation (2.5pp). Manufacturing and Public Service IRCs have no significant relationship to employment, and

IRCs in the remaining four clusters decrease employment probability: Arts (-1.1pp), Business (-1.5pp), Human Services (-2.7pp), and IT (-3.2pp). In terms of wages, IRCs in seven career clusters increase quarterly wages: Agriculture (7.4%), Construction (30.4%), Education (23.8%), Health (6.2%), Hospitality (19.5%), Manufacturing (7.1%), and Transportation (33.0%). Public Service IRCs have no significant relationship, and IRCs in all other subject areas are associated with a drop in wages: Arts (-11.6%), Business (-13.4%), Human Services (-17.3%), and IT (-28.0%). Finally, Education IRCs are associated with 3.8pp greater job stability, followed by Transportation and Construction IRCs. On the reduced job stability side, we observe IT IRCs associated with 3pp reduction in job stability, followed by Human Services and Business IRCs.

[Table 4]

3.3. Outcomes by Demographic Groups

We also run equation (1) separately for each racial/ethnic, gender, and income group, and present the findings on employment and log wages in Tables 5 and 6, respectively. In Table 5, our findings suggest attaining an IRC meaningfully raises employment probability by 0.9pp for White students and 0.3pp for male students, and decreases by 0.3pp for Female students. Aligned IRCs are mostly related to employment gain – Asian, Black, Hispanic and White students earning an aligned IRC are 2.1pp, 1.2pp, 1.1pp and 1.6pp more likely to be employed than those earning no IRC, respectively. Male recipients are 1.7pp more likely to be employed than comparable male students with no IRC, and female recipients are 0.7pp more likely. Low-income students 1.3pp more likely to be employed with an aligned IRC, whereas non-low-income students are 1.1pp more likely. However, misaligned IRCs are inversely associated with employment for only Hispanic, female, non-low-income and low-income students. Interestingly, female students lose more by earning a misaligned IRC than they gain

from an aligned IRC. Additional IRCs only help Asian, White, male, and low-income students' employment probability by 0.2-0.5pp.

As we look into the cluster analysis, Agriculture IRCs increase employment probability by 1.2pp for Hispanic students, by 1.0pp for female students, and 0.9pp for low-income students. Business IRCs hurt all groups' employment probability, while Construction IRCs help all groups. Education IRCs improve employment for male, female, and low-income students. Health IRCs improve employment for Hispanic and low-income students. Hospitality IRCs help Asian, students of other races, and White students get employment as well as students of all income and gender groups. Human Services IRCs have different effects by groups – Hispanic, male, female, and low-income students have negative employment coefficient ranging between -2.2-10.4pp, whereas White and non-low-income students on the contrary gain by almost 4.6pp and 3.8pp respectively. IT IRCs decrease employment probability for all groups. Manufacturing IRCs hurt Asian, Hispanic, and female students' employment probability. Public Services IRCs only improve employment probability for Black students. Finally, Transportation IRCs having the largest overall employment effect helps all groups except for Asian students, students of other races and female students. The gains range between 1.5-4.3pp with Black students reporting the largest gain. When considered within each demographic group, Asian students and Other races with a Hospitality IRC, Black, Hispanic, White, and male students with a Transportation IRC, female students with an Education IRC, both non-low-income and low-income students with a Construction IRC report the highest employment gains than no or other IRC recipients in the same group.

Table 6 presents the log wages separately by groups. Earning an IRC is associated with an increase in wages by 7.9% for Asian students, 10.9% for White students, 8.0% for males, and

a roughly 4% increase for low and non-low-income students. Similar to the employment outcome, aligned IRCs increase wages for all groups by 10-22%, the most for Asian, White, male, and low-income students. Misaligned IRCs are associated with wage loss for Hispanic and female students, but wage gain for White, and male students. Additional IRCs help raise wages by 1.8-6.6%, except for female students, who experience wage loss of 2.8%. The wage by cluster analysis mostly aligns with the employment analysis. Notably, Construction IRCs are associated with 18.0-75.7% gains in wages, Hospitality IRCs with 13.6-67.9% gains, and Transportation IRCs with 22.9-51.2% gains.

4. Discussion

Both the federal government and a growing number of states have increasingly incentivized students' receipt of IRCs to ensure they can demonstrate their possession of knowledge and skills aligned with in-demand, high-skill occupations. In theory, this strategy may be particularly beneficial for non-college-bound students and those who have historically experienced greater precarity in the labor market, such as students of color, low-income students, and women. Indeed, scholars have argued for increased investments in workforce preparation like IRCs given low rates of college and labor market success experienced by many high school graduates (Rosenbaum et al. 2015; Rosenbaum 2001). Despite the tremendous growth in IRCs earned by K-12 students – up to one-third of high school graduates in states like Texas now earn IRCs – limited research has examined whether IRCs produce “sheepskin effects” and improve students' labor market outcomes, above and beyond their CTE and other coursetaking (Baird, Bozick, and Zaber 2022; Giani 2022; Hendricks et al. 2021; Xu et al. 2024).

The evidence produced by our analyses shows that the relationship between students' receipt of IRCs in high school and their early labor outcomes is decidedly mixed. On the positive

side, we find that IRC receipt is associated with a roughly 9% increase in quarterly wages on average. This estimate is larger than the estimated benefit of each additional CTE course students complete (6%) and smaller than the estimated benefit of concentrating in a CTE subject (23%) (i.e., their completion of three CTE courses in the same subject). If the typical recent high school graduate earns \$20,000/year, earning an IRC amounts to a \$1,000/year increase in wages. Given that over 100,000 of the roughly 350,000 high school graduates in Texas each year earn an IRC, increasing each IRC recipient's annual wages by \$1,000 translates into \$100M in increased annual wages for each graduating cohort.

Consistent with prior literature, we find that the benefits of IRC receipt vary between subjects (D. Xu et al. 2024; Giani 2022). IRCs earned in CTE clusters such as Construction, Education, Health, Hospitality, and Transportation are positively and significantly related to both employment (1-2pp) and earnings (6-34%). IRCs earned in Construction and Transportation are associated with 30% and 33% increases in earnings, respectively, and IRCs in Education are associated with 8pp increases in employment stability. Overall, these findings align with prior research on the heterogeneous labor returns to K-12 CTE coursework and sub-baccalaureate credentials earned at community and technical colleges (Z. Xu and Backes 2023; Olivera-Aguilar et al. 2022; Broderson et al. 2021; Ecton and Dougherty 2023; Carruthers et al. 2024).

Despite these positive findings, our analyses show that the benefits of IRCs are unevenly distributed. Critically, in states such as Texas, students do not have to earn IRCs while completing CTE programs of study for the IRCs to count in the state accountability system. Prior research has found that the majority of IRCs earned by Texas students – up to 75% in more recent cohorts – are indeed misaligned with their CTE coursework (Giani et al., 2025). Whereas

aligned IRCs are positively and significantly related to students' employment and earnings in our analyses, we find that misaligned IRCs produce essentially no benefit. Indeed, the 9% average earnings boost for all IRC recipients can be decomposed into a 27% increase in earnings for the one-third of students in our sample who earned an aligned IRC and a 0% increase for the other two-thirds who earned a misaligned IRC. These results support the conclusion reached in prior research that high schools may be using IRC attainment to game the accountability system, rather than to provide students with rigorous and valuable credentials that can improve their labor outcomes (Giani et al., 2025). These results also suggest that the sheepskin effects of IRCs may only be produced if IRCs are aligned with students' CTE pathways.

Even more concerning, while IRCs have been conceptualized as an equity-promoting strategy that can disproportionately improve the labor market position of students from populations historically marginalized from good jobs, our results suggest the opposite is occurring. Prior research has found that IRC participation varies across gender, race, student achievement levels (Giani 2022; Walsh et al. 2019; Eagan and Koedel 2021; Glennie, Lauff, and Ottem 2017) and the relationships between IRC receipt and postsecondary and workforce outcomes vary across IRC subject area (D. Xu et al. 2024; Giani 2022). Our findings extend this line of research to the benefits of any, aligned, and number of IRCs.

Among racial/ethnic groups, White students receive the greatest average benefit from IRC receipt, whereas Hispanic/Latino students – the majority of the K-12 population in Texas – receive no benefit. While all racial/ethnic groups receive considerable benefits from aligned IRCs, White students are the only group that receives an earnings boost from misaligned IRCs, whereas misaligned IRC receipt is associated with a decline in wages for Hispanic/Latino students. Similarly, male students receive greater benefits of IRCs compared to females,

regardless of whether the certifications are aligned with their CTE coursework or not. Low-income students receive no benefit from misaligned IRCs, whereas non-low-income students do. Overall, the benefits of IRCs tend to accrue to students from populations that have historically fared better in the labor market. In Texas at least, IRCs are conducive to labor market inequity.

5. Limitations and Future Research

Although our study is one of the first to estimate the sheepskin effects of IRCs and examine heterogeneity in the benefits of IRCs across subjects, CTE-IRC alignment, and demographic groups, there are a number of limitations of our study that should be addressed in future research. We caution against drawing causal conclusions about the effects of IRCs from our analyses. While the CRE methods we used allow us to control for individual student fixed effects, the fact that IRCs are not time-varying across post-HS periods in our data prevented us from examining how changes in IRC receipt over time relates to changes in labor outcomes. If students who earn IRCs are systematically different on unobserved characteristics compared to students who do not, our estimates could still be biased. Future research using alternative methods to estimate the value of IRCs is warranted.

Research has tended to show a tradeoff between the short-term labor market benefits of vocational and technical education and the long-term benefits of higher education (Hanushek et al., 2017). Although our results suggest at least some IRCs are positively associated with students' employment and earnings within the first few years after graduating from high school, future research would be needed to examine whether these labor market benefits are sustained over time or fade out as the outcomes of students who did not earn IRCs improve at a faster rate.

Finally, while the state administrative data used in this study allowed us to examine the employment and earnings outcomes for entire cohorts of high school graduates, limitations of this data should be borne in mind. Students who leave the state cannot be tracked in the data, which could bias our estimates in unknown ways. For example, our estimates of the value of IRCs could be biased upwards if students who earn IRCs are more likely to work in Texas and students who move to other states do so to secure better jobs and earn higher pay. Additionally, although we are able to examine employment and earnings, we are not able to examine other important outcomes, such as actual rates of pay and the occupations students enter. One assumption of IRCs is that they are aligned with specific occupations, many of which require students to earn credentials in order to work in those positions (e.g., cosmetologists, certified nursing assistants). Expanding state administrative data systems to include data such as hours worked/hourly pay and occupational codes would expand possibilities for the types of research on the benefits of IRCs that could be pursued.

6. References

- Advance CTE. 2025a. Dashboard: State Approaches to Credentialing.
- . 2025b. *The State of Career Technical Education: Credentials of Value*.
https://careertech.org/wp-content/uploads/2025/06/8011_StateOfCTE_Full_508_052825.pdf.
- Albert, Kyle. 2017. "The certification earnings premium: An examination of young workers." *Social Science Research* 63: 138-149.
- Allison, Paul D. 2009. *Fixed effects regression models*. SAGE publications.
- Backes, Ben, Harry J Holzer, and Erin Dunlop Velez. 2015. "Is it worth it? Postsecondary education and labor market outcomes for the disadvantaged." *IZA Journal of Labor Policy* 4 (1): 1.
- Baird, Matthew D, Robert Bozick, and Melanie A Zaber. 2022. "Beyond traditional academic degrees: The labor market returns to occupational credentials in the United States." *IZA Journal of Labor Economics* 11 (1).
- Baum, S. 2014. *Higher education earnings premium: Value, variation, and trends*. Urban Institute (Washington, DC).
<https://www.urban.org/sites/default/files/publication/22316/413033-Higher-Education-Earnings-Premium-Value-Variationand-Trends.PDF>.
- Becker, Gary S. 1962. "Investment in human capital: A theoretical analysis." *Journal of political economy* 70 (5, Part 2): 9-49.
- . 1975. *Human capital: a theoretical and empirical analysis, with special reference to education*. University of Chicago Press Chicago.
- Belfield, Clive, and Thomas Bailey. 2017. "The Labor Market Returns to Sub-Baccalaureate College: A Review. A CAPSEE Working Paper." *Center for Analysis of Postsecondary Education and Employment*.
- Broderson, R Marc, Douglas Gagnon, Jing Liu, and Steven Tedeschi. 2021. "The impact of career and technical education on postsecondary outcomes in Nebraska and South Dakota." *National Center for Education Evaluation and Regional Assistance*.
<https://files.eric.ed.gov/fulltext/ED612630.pdf>.
- Brunner, Eric J, Shaun M Dougherty, and Stephen L Ross. 2023. "The effects of career and technical education: Evidence from the Connecticut technical high school system." *Review of Economics and Statistics* 105 (4): 867-882.
- Carnevale, Anthony P, Stephen J Rose, and Andrew R Hanson. 2012. "Certificates: Gateway to Gainful Employment and College Degrees." *Georgetown University Center on Education and the Workforce*.
- Carruthers, Celeste K, Shaun Dougherty, Thomas Goldring, Daniel Kreisman, Roddy Theobald, Carly Urban, and Jesús Villero. 2024. "Who Takes High-Earning CTE Pathways?"
- Clark, Damon, and Paco Martorell. 2014. "The signaling value of a high school diploma." *Journal of Political Economy* 122 (2): 282-318.
- Credential Engine. "Bringing Credential Transparency Through Technology."
<https://credentialengine.org/about-us/>.
- Cunningham, Evan. 2019. "Professional certifications and occupational licenses." *Monthly Labor Review*: 1-38.

- Dadgar, Mina, and Madeline Joy Trimble. 2015. "Labor market returns to sub-baccalaureate credentials: How much does a community college degree or certificate pay?" *Educational Evaluation and Policy Analysis* 37 (4): 399-418.
- Dalton, Ben, Elizabeth J Glennie, Roger Studley, Siri Warkentien, and Erich Lauff. 2021. "Do high school industry certifications reflect local labor market demand? An examination of Florida." *Career and Technical Education Research* 46 (2): 3-22.
- Darling-Hammond, Linda, Gene Wilhoit, and Linda Pittenger. 2014. "Accountability for college and career readiness: Developing a new paradigm." *Education policy analysis archives* 22: 86-86.
- Díaz, María Mercedes Mateo-Berganza, JungKyu Rhys Lim, Isabel Cardenas Navia, and Karen Elzey. 2022. "A world of transformation: Moving from degrees to skills-based alternative credentials."
- Dougherty, Shaun M. 2018. "The effect of career and technical education on human capital accumulation: Causal evidence from Massachusetts." *Education Finance and Policy* 13 (2): 119-148.
- Eagan, Joshua, and Cory Koedel. 2021. "Career Readiness in Public High Schools: An Exploratory Analysis of of Industry Recognized Credentials. Working Paper No. 257-0921." *National Center for Analysis of Longitudinal Data in Education Research (CALDER)*.
- Ecton, Walter G, and Shaun M Dougherty. 2023. "Heterogeneity in high school career and technical education outcomes." *Educational Evaluation and Policy Analysis* 45 (1): 157-181.
- Education Commission of the States. 2023. *Secondary Career and Technical Education 2023*. <https://reports.ecs.org/comparisons/secondary-career-and-technical-education-2023-08>.
- Ferrer, Ana M, and W Craig Riddell. 2001. "Sheepskin effects and the returns to education." *Towards Evidence-Based Policy for Canadian Education*: 423-45.
- Fuller, Joseph B, Christina Langer, Julia Nitschke, Layla O'Kane, Matt Sigelman, and Bledi Taska. 2022. *The emerging degree reset*. <https://static1.squarespace.com/static/6197797102be715f55c0e0a1/t/6202bda7f1ceee7b0e9b7e2f/1644346798760/The+Emerging+Degree+Reset+%2822.02%29Final.pdf>.
- Giani, Matthew. 2022. "How Attaining Industry-Recognized Credentials in High School Shapes Education and Employment Outcomes." *Thomas B. Fordham Institute*.
- Giani, Matthew, Madison E. Andrews, Tasneem Sultana, and Fortunato Medrano. 2025. "Curricular-Credential Decoupling: How Schools Respond to Career and Technical Education Policy." *EdWorkingPaper* 25 (1128). <https://doi.org/10.26300/he7x-3a63>.
- Glennie, Elizabeth J, Erich Lauff, and Randy Ottem. 2017. "Examining the Influence of the Florida" Career and Professional Education Act of 2007": Changes in Industry Certifications and Educational and Employment Outcomes." *Office of Career, Technical, and Adult Education, US Department of Education*.
- Glennie, Elizabeth J, Erich Lauff, Roger Studley, and Ben Dalton. 2023. "Pathways to Credentials: Does the Timing of Earning an Industry Certification in High School Influence Postsecondary Educational Outcomes?" *Journal of Research in Technical Careers* 7 (1): 45.
- Glennie, Elizabeth J, Randolph Ottem, and Erich Lauff. 2020. "The Influence of Earning an Industry Certification in High School on Going to College: The Florida CAPE Act." *Journal of Career and Technical Education* 35 (1): 17-35.

- Hackmann, Donald G, Joel R Malin, and Debra D Bragg. 2019. "An analysis of college and career readiness emphasis in ESSA state accountability plans." *Education Policy Analysis Archives* 27: 160-160.
- Hanushek, Eric A, Guido Schwerdt, Ludger Woessmann, and Lei Zhang. 2017. "General education, vocational education, and labor-market outcomes over the lifecycle." *Journal of human resources* 52 (1): 48-87.
- Hendricks, Anjanette, Steve Myran, Petros J Katsioloudis, William Owings, and Leslie Kaplan. 2021. "Career and Technical Education Industry Credentials and Its Potential Impact on a State's Economy." *Online Submission* 23 (8): 1-10.
- Hout, Michael. 2012. "Social and economic returns to college education in the United States." *Annual review of sociology* 38 (1): 379-400.
- Hungerford, Thomas, and Gary Solon. 1987. "Sheepskin effects in the returns to education." *The review of economics and statistics*: 175-177.
- Jaeger, David A, and Marianne E Page. 1996. "Degrees matter: New evidence on sheepskin effects in the returns to education." *The review of economics and statistics*: 733-740.
- Jepsen, Christopher, Kenneth Troske, and Paul Coomes. 2014. "The labor-market returns to community college degrees, diplomas, and certificates." *Journal of Labor Economics* 32 (1): 95-121.
- Kreisman, Daniel, and Kevin Stange. 2020. "Vocational and career tech education in American high schools: The value of depth over breadth." *Education Finance and Policy* 15 (1): 11-44.
- Layard, Richard, and George Psacharopoulos. 1974. "The screening hypothesis and the returns to education." *Journal of political economy* 82 (5): 985-998.
- Lindsay, Jim, Katherine Hughes, Shaun M Dougherty, Kelly Reese, and Megha Joshi. 2024. "What We Know About the Impact of Career and Technical Education: A Systematic Review of the Research."
- Mincer, Jacob A. 1974. "Schooling and earnings." In *Schooling, experience, and earnings*, 41-63. NBER.
- National Center for Education Statistics. 2024. *Postsecondary Certificates and Degrees Conferred*. (Condition of Education: Institute of Education Sciences. U.S. Department of Education). <https://nces.ed.gov/programs/coe/indicator/cts>.
- Olivera-Aguilar, Margarita, Harrison J Kell, Chelsea Ezzo, and Steven B Robbins. 2022. "Investigating the Relationship Between Career and Technical Education High School Course-Taking and Early Job Outcomes." *ETS Research Report Series* 2022 (1): 1-18.
- Park, Jin Heum. 1999. "Estimation of sheepskin effects using the old and the new measures of educational attainment in the Current Population Survey." *Economics Letters* 62 (2): 237-240.
- Pascarella, Ernest T, and Patrick T Terenzini. 2005. *How College Affects Students: A Third Decade of Research. Volume 2*. ERIC.
- Pew Research Center. 2024. *Is College Worth It?* https://www.pewresearch.org/social-trends/2024/05/23/is-college-worth-it-2/?utm_source=AdaptiveMailer&utm_medium=email&utm_campaign=24-05-23%20-%20GENERAL%20Adults%20Without%20College%20Degrees&org=982&lvl=100&ite=14015&lea=3428872&ctr=0&par=1&trk=a0DQm000001sHWLMA2.

- Psacharopoulos, George, and Harry Anthony Patrinos. 2018. "Returns to investment in education: a decennial review of the global literature." *Education Economics* 26 (5): 445-458.
- Rodríguez, Jhon James Mora, and Juan Muro. 2015. "On the size of sheepskin effects: A meta-analysis." *Economics* 9 (1): 20150037.
- Rosenbaum, James. 2001. *Beyond college for all: Career paths for the forgotten half*. Russell Sage Foundation.
- Rosenbaum, James, Caitlin Ahearn, Kelly Becker, and Janet Rosenbaum. 2015. "The New Forgotten Half and Research Directions to Support Them. A William T. Grant Foundation Inequality Paper." *William T. Grant Foundation*.
- Schunck, Reinhard. 2013. Within and between estimates in random-effects models: Advantages and drawbacks of correlated random effects and hybrid models. *The Stata Journal*, 13 (1), 65-76.
- Spence, A Michael. 1974. "Market signaling: Informational transfer in hiring and related screening processes." (*No Title*).
- Texas Education Agency. 2024. "Industry-Based Certifications." Accessed 2/1/2024. <https://tea.texas.gov/academics/college-career-and-military-prep/career-and-technical-education/industry-based-certifications>.
- Walsh, Matthew, Layla O'Kane, Gilberto Noronha, and Bledi Taska. 2019. "Where Credentials Meet the Market: State Case Studies on the Effect of High School Industry Credentials on Educational and Labor Market Outcomes." *Foundation for Excellence in Education (ExcelinEd)*.
- Wooldridge, Jeffrey M. 2019. "Correlated random effects models with unbalanced panels." *Journal of Econometrics* 211 (1): 137-150.
- Xu, Di, Kelli A Bird, Michael Cooper, and Benjamin L Castleman. 2024. "Noncredit Workforce Training, Industry Credentials, and Labor Market Outcomes. EdWorkingPaper No. 24-959." *Annenberg Institute for School Reform at Brown University*.
- Xu, Di, and Madeline Trimble. 2016. "What about certificates? Evidence on the labor market returns to nondegree community college awards in two states." *Educational Evaluation and Policy Analysis* 38 (2): 272-292.
- Xu, Zeyu, and Ben Backes. 2023. "Linkage between fields of focus in high school career technical education and college majors." *Educational Evaluation and Policy Analysis*: 01623737231164149.

Tables and Figures

Table 1: Variable Description and Summary Statistics

Name	Description	Observations ¹	Mean (SD)
Panel A: Student level variables (<i>N</i> = 1,698,846)			
<i>Demographics</i>			
Race/Ethnicity			
Asian	Indicator for a student identifying as Asian	63,963	0.038 (0.190)
Black	Indicator for a student identifying as African American	223,710	0.132 (0.338)
Hispanic	Indicator for a student identifying as Hispanic/Latino	837,980	0.493 (0.500)
Non-Hispanic White	Indicator for a student identifying as Non-Hispanic White	529,126	0.311 (0.463)
Others	Indicator for students with Multiracial/Native American/Native Hawaiian and Pacific Islander or Other ethnicities than those listed	44,067	0.026 (0.159)
Gender			
Male	Indicator for a student identifying as male	838,305	0.493 (0.500)
Female	Indicator for a student identifying as female	860,541	0.507 (0.500)
Income indicators			
Low-income	Indicator for students qualifying for Free or Reduced-Price Lunch or similar federal assistance, as listed by TEA	1,141,981	0.672 (0.469)
Non low-income	Indicator for students not classified as low-income	556,865	0.328 (0.469)
Gifted status			
Not gifted	Indicator for students not gifted	1,536,439	0.904 (0.294)
Gifted	Indicator for students performing at an ability higher than their age	162,407	0.096 (0.294)
Special Education			
Yes	Indicator for students with some disability	1,578,457	0.929 (0.257)
No	Indicator for students with no known disability	120,389	0.071 (0.257)
ESL status			
Non-ESL	Indicator for not participating in ESL	1,611,706	0.949 (0.221)
ESL	Indicator for participating in ESL	87,140	0.051 (0.221)
<i>High School Graduation Year</i>			
2017	Indicator for students graduating HS in 2017	284,434	0.167 (0.373)
2018	Indicator for students graduating HS in 2018	294,051	0.173 (0.378)
2019	Indicator for students graduating HS in 2019	295,187	0.174 (0.379)
2020	Indicator for students graduating HS in 2020	290,653	0.171 (0.377)
2021	Indicator for students graduating HS in 2021	276,700	0.163 (0.369)
2022	Indicator for students graduating HS in 2022	257,821	0.152 (0.359)
<i>High school exit profile</i>			
CTE Completers	Indicator for students completing 3 or more CTE credits in one career field	616,294	0.363 (0.481)
CTE Concentrators	Indicator for students completing 2 or more CTE credits in one career field	1,105,012	0.650 (0.477)

CTE Participators	Indicator for students completing 1 or more CTE credits	1,621,242	0.954 (0.209)
<i>IRC measures</i>			
Any IRC	Indicator for a student earning an IRC	209,007	0.123 (0.328)
Aligned IRC	Indicator for a student earning an IRC aligned with their CTE concentration (only for any IRC subsample)	69,207	0.331 (0.471)
<i>IRC Clusters</i>			
Arts	Indicator for an IRC in Arts, and Audio and Visuals	27,577	0.016 (0.126)
Agriculture	Indicator for an IRC in Agriculture	14,029	0.008 (0.091)
Business, Finance, and Marketing	Indicator an IRC in Business, Finance, and Marketing	63,609	0.037 (0.190)
Construction	Indicator for an IRC in Architecture and Construction	17,113	0.010 (0.100)
Human Services	Indicator for an IRC in Human Services	1,617	0.001 (0.031)
Education	Indicator for a student completing an IRC in Education	35,714	0.021 (0.143)
Information Technology	Indicator for a student completing an IRC in Information Technology	6,666	0.004 (0.063)
Health	Indicator for a student completing an IRC in Health Sciences	5,630	0.003 (0.058)
Hospitality	Indicator for a student completing an IRC in Hospitality and Tourism	2,776	0.002 (0.040)
Manufacturing	Indicator for a student completing an IRC in Manufacturing	27,381	0.016 (0.126)
Public Services	Indicator for a student completing an IRC in the Public Services	14,240	0.008 (0.091)
Transportation	Indicator for a student completing an IRC in Transportation	9,982	0.006 (0.076)
Panel B: Quarterly variables ($N = 20,435,730$)			
<i>Labor market outcomes</i>			
Employed	Indicator for a student being employed		0.660 (0.474)
Quarterly wages	Total Wage in a fiscal quarter, reported by TWC-indexed at 2019 Consumer Price Index (CPI)	6,647.890	(12100.400)
Quarterly log wages	Natural logarithm of quarterly wages		8.359 (1.130)
Age	Continuous measure of student's age at every fiscal quarter		19.746 (1.740)
<i>Educational measures</i>			
Highest credential completed (in a FQ)			
HS Diploma	Indicator for a student having a HS diploma or an IRC	17,444,814	0.854 (0.353)
Level 0 Certifications	Indicator for a student having a certificate ranging between 1-15 credits	195,466	0.010 (0.097)
Level 1 Certifications	Indicator for a student having a certificate taking less than a year to complete	264,309	0.013 (0.113)
Level 2 Certifications	Indicator for a student having a certificate 1-2 years to complete	71,314	0.003 (0.059)
Applied/Technical Associates	Indicator for a student having an Associates degree in Technical or Applied track	208,757	0.010 (0.101)
Academic Associates	Indicator for a student having an Associates degree in academic track	714,386	0.035 (0.184)
Applied/Technical Bachelors	Indicator for a student having a Bachelor's degree in Technical or Applied track	3,243	0.000 (0.013)
Academic Bachelors	Indicator for a student having a Bachelor's degree in academic track	1,470,500	0.072 (0.258)
Graduate level Certificate	Indicator for a student having a Certificate considered equivalent to a graduate level degree in academic track	320	0.000 (0.004)
Master's	Indicator for a student having a Master's degree	61,269	0.003 (0.055)

Doctoral (Professional)	Indicator for a student having a Doctoral degree in Professional track	1,186	0.000 (0.008)
Doctoral (Academic)	Indicator for a student completed a Doctoral degree in Professional track	166	0.000 (0.003)
College credits attempted	Number of credits a student is enrolled in college		3.383 (7.013)
Years since high school graduation	Number of years that have passed since the student graduated from HS		2.567 (1.617)

Notes. ¹Equal to sample size (N) unless otherwise noted.

Table 2: Descriptives by IRC Attainment

	No IRC	Any IRC	Aligned IRC	Misaligned IRC
<i>Demographics</i>				
Race/Ethnicity				
Asian	0.032 (0.176)	0.032 (0.177)	0.040 (0.195)	0.028 (0.166)
Black	0.139 (0.346)	0.085 (0.279)	0.088 (0.283)	0.084 (0.277)
Hispanic	0.490 (0.500)	0.570 (0.495)	0.585 (0.493)	0.561 (0.496)
Non-Hispanic White	0.312 (0.464)	0.292 (0.455)	0.265 (0.442)	0.306 (0.461)
Others	0.026 (0.158)	0.021 (0.143)	0.021 (0.145)	0.021 (0.142)
Male	0.508 (0.500)	0.537 (0.499)	0.404 (0.491)	0.609 (0.488)
Female	0.492 (0.500)	0.463 (0.499)	0.596 (0.491)	0.391 (0.488)
Low-income	0.679 (0.467)	0.722 (0.448)	0.716 (0.451)	0.725 (0.447)
Non-low-income	0.321 (0.467)	0.278 (0.448)	0.284 (0.451)	0.275 (0.447)
<i>High school exit profile</i>				
CTE credits	4.543 (2.598)	6.116 (2.485)	6.571 (1.958)	5.870 (2.696)
Non-CTE credits	20.669 (4.532)	20.055 (3.763)	20.238 (3.298)	19.956 (3.987)
CTE Completers	0.319 (0.466)	0.608 (0.488)	1.000 (0.000)	0.397 (0.489)
CTE Concentrators	0.616 (0.486)	0.870 (0.336)	1.000 (0.000)	0.800 (0.400)
CTE Participants	0.951 (0.216)	0.994 (0.075)	1.000 (0.000)	0.991 (0.093)
HS Graduation Cohort				
2017	0.297 (0.457)	0.086 (0.281)	0.104 (0.305)	0.077 (0.266)
2018	0.249 (0.433)	0.134 (0.340)	0.182 (0.386)	0.107 (0.310)
2019	0.190 (0.392)	0.224 (0.417)	0.244 (0.430)	0.214 (0.410)
2020	0.139 (0.346)	0.216 (0.411)	0.198 (0.398)	0.225 (0.418)
2021	0.086 (0.280)	0.189 (0.391)	0.159 (0.366)	0.205 (0.404)
2022	0.038 (0.192)	0.151 (0.358)	0.113 (0.316)	0.172 (0.377)
<i>Postsecondary Outcomes</i>				
Employment	0.658 (0.474)	0.689 (0.463)	0.701 (0.458)	0.682 (0.466)
Quarterly wages (in \$1,000)	6.622 (12.393)	6.915 (8.548)	6.673 (5.570)	7.049 (9.814)
Quarterly log wages	8.351 (1.134)	8.434 (1.085)	8.406 (1.074)	8.449 (1.091)
Highest credential completed				
HS Diploma	0.852 (0.355)	0.866 (0.341)	0.836 (0.370)	0.882 (0.322)
Level 0 Certifications	0.010 (0.097)	0.009 (0.096)	0.012 (0.111)	0.008 (0.087)
Level 1 Certifications	0.012 (0.107)	0.027 (0.162)	0.024 (0.152)	0.029 (0.168)
Level 2 Certifications	0.003 (0.059)	0.004 (0.061)	0.004 (0.065)	0.003 (0.059)
Applied/Technical Associates	0.010 (0.100)	0.012 (0.109)	0.013 (0.113)	0.011 (0.106)
Academic Associates	0.035 (0.184)	0.034 (0.181)	0.044 (0.205)	0.029 (0.167)
Applied/Technical Bachelors	0.000 (0.012)	0.000 (0.015)	0.000 (0.016)	0.000 (0.014)
Academic Bachelors	0.074 (0.262)	0.046 (0.210)	0.065 (0.247)	0.036 (0.187)
Graduate level Certificate	0.000 (0.004)	0.000 (0.003)	0.000 (0.005)	0.000 (0.000)
Master's	0.003 (0.056)	0.001 (0.036)	0.001 (0.036)	0.001 (0.036)
Doctoral (Professional)	0.000 (0.008)	0.000 (0.003)	0.000 (0.005)	0.000 (0.000)
Doctoral (Academic)	0.000 (0.003)	0.000 (0.002)	0.000 (0.000)	0.000 (0.003)
College credits attempted	3.289 (6.874)	4.382 (8.296)	4.965 (8.424)	4.067 (8.208)
<i>N</i>	18,688,237	1,747,493	612,337	1,135,156

Notes. This table presents the demographic and academic differences by IRC attainment and alignment. The first value corresponds to the mean difference, and the value in parenthesis contains the standard deviation (SD). For example, column (2) in row (3) represents the mean and SD for Asian students with no IRC and reads as 3.2% Asian students in our sample do not have an IRC. Aligned and Misaligned IRCs are conditional on earning any IRC. Sources: TERC, 2014-2023.

Table 3: Relationship Between IRC Receipt and Quarterly Employment, Log Wages, and Employment Stability

	Any IRC			Aligned IRC			IRC count		
	Emp.	Log Wages	Emp. Stability	Emp.	Log Wages	Emp. Stability	Emp.	Log Wages	Emp. Stability
<i>IRCs</i>									
Any	0.001 (0.001)	0.087*** (0.007)	0.002** (0.001)						
Aligned				0.013*** (0.001)	0.147*** (0.012)	0.013*** (0.001)			
Misaligned				-0.005*** (0.001)	-0.009 (0.008)	-0.003** (0.001)			
Count							0.000 (0.001)	0.032*** (0.005)	0.002*** (0.001)
<i>Sheepskin Controls</i>									
Non-CTE	0.000*** (0.000)	0.009*** (0.001)	0.001*** (0.000)	0.000*** (0.000)	0.006*** (0.001)	0.001*** (0.000)	0.000*** (0.000)	0.006*** (0.001)	0.001*** (0.000)
Credits									
CTE Credits	0.007*** (0.000)	0.055*** (0.001)	0.007*** (0.000)	0.007*** (0.000)	0.066*** (0.001)	0.007*** (0.000)	0.007*** (0.000)	0.065*** (0.001)	0.007*** (0.000)
CTE	0.003*** (0.001)	0.228*** (0.004)	0.005*** (0.001)	0.001* (0.001)	0.032*** (0.006)	0.004*** (0.001)	0.003*** (0.001)	0.046*** (0.005)	0.005*** (0.001)
Concentrator									
Overall R-Sq	0.024	0.044	0.054	0.024	0.039	0.054	0.024	0.039	0.054
ICC	0.405	0.359	0.368	0.405	0.448	0.368	0.405	0.448	0.368
Observations	20,435,730	18,860,879	19,734,482	20,435,730	20,435,730	19,734,482	20,435,730	20,435,730	19,734,482

* p < 0.05, ** p < 0.01, *** p < 0.001

Note. This table presents students' postsecondary labor market outcomes by any IRC attainment, an aligned or misaligned IRC, and number of IRCs, as compared to those not having any IRC. Columns 1, 4, and 7 represent employment estimates; even columns 2, 5, and 8 represent log wage; and columns 3, 6, and 9 represent employment stability estimates. All the models include the following controls: highest credential attained, demographics (i.e., race, gender, income status, special education, gifted status, and ESL indicators), HS CTE and non-CTE credits, CTE concentrator, college credits attempted per fiscal quarter, year-quarter fixed effects, and HS graduation year fixed effects. We clustered the standard errors at the student level.

Table 4: Relationship Between IRC Cluster and Quarterly Employment, Log Wages, and Stability

	Emp.	Log Wages	Emp. Stability
<i>IRC Clusters</i>			
Agriculture	0.006*** (0.002)	0.074*** (0.019)	0.009*** (0.002)
Arts	-0.011*** (0.003)	-0.116*** (0.026)	-0.012*** (0.003)
Business, Finance, and Marketing	-0.015*** (0.001)	-0.134*** (0.013)	-0.015*** (0.002)
Construction	0.025*** (0.003)	0.304*** (0.023)	0.028*** (0.003)
Education	0.028*** (0.008)	0.238** (0.073)	0.038*** (0.009)
Health	0.004* (0.002)	0.062*** (0.016)	0.005*** (0.002)
Hospitality	0.019*** (0.004)	0.195*** (0.037)	0.022*** (0.005)
Human Services	-0.027*** (0.005)	-0.173*** (0.040)	-0.024*** (0.005)
IT	-0.032*** (0.007)	-0.280*** (0.057)	-0.033*** (0.007)
Manufacturing	-0.003 (0.002)	0.071*** (0.019)	0.002 (0.002)
Public Services	-0.001 (0.003)	-0.025 (0.026)	-0.004 (0.003)
Transportation	0.025*** (0.003)	0.330*** (0.032)	0.033*** (0.004)
Overall R-Sq	0.025	0.040	0.054
ICC	0.405	0.448	0.368
Observations	20,435,730	20,435,730	19,734,482

* p < 0.05, ** p < 0.01, *** p < 0.001

Note. This table presents students' postsecondary labor market outcomes by IRC type/cluster, as compared to students who did not earn any IRC. All the models include the following controls: highest credential attained, demographics (i.e., race, gender, income status, special education, gifted status, and ESL indicators), HS CTE and non-CTE credits, CTE concentration cluster, college credits attempted per fiscal quarter, year-quarter fixed effects, and HS graduation year fixed effects. We clustered the standard errors at the student level.

Table 5: Relationship Between IRC Receipt and Quarterly Employment by Demographics

	Asian	Black	Hispanic	Other Races	White	Male	Female	Non-Low-I ncome	Low-Income
<i>Overall IRCs</i>									
Any IRC	0.006 (0.004)	-0.001 (0.003)	-0.002 (0.001)	-0.000 (0.006)	0.006*** (0.002)	0.004** (0.001)	-0.004*** (0.001)	0.000 (0.002)	0.001 (0.001)
Aligned IRC	0.022** (0.007)	0.010* (0.004)	0.013*** (0.002)	0.007 (0.009)	0.016*** (0.003)	0.021*** (0.002)	0.006*** (0.002)	0.011*** (0.003)	0.015*** (0.002)
Misaligned IRC	-0.003 (0.006)	-0.006 (0.003)	-0.009*** (0.001)	-0.004 (0.007)	0.002 (0.002)	-0.002 (0.001)	-0.011*** (0.001)	-0.005** (0.002)	-0.006*** (0.001)
IRC Count	0.006* (0.003)	-0.001 (0.002)	0.000 (0.001)	0.003 (0.004)	0.002* (0.001)	0.003*** (0.001)	-0.005*** (0.001)	0.000 (0.001)	0.001 (0.001)
<i>IRC Clusters</i>									
Agriculture	0.012 (0.013)	-0.002 (0.006)	0.012*** (0.003)	-0.000 (0.014)	0.001 (0.003)	-0.000 (0.004)	0.010*** (0.003)	0.000 (0.004)	0.009*** (0.003)
Arts	-0.005 (0.014)	-0.031** (0.010)	-0.008* (0.004)	-0.010 (0.018)	-0.008 (0.005)	-0.004 (0.004)	-0.021*** (0.005)	-0.009 (0.005)	-0.011** (0.004)
BMF	-0.008 (0.007)	-0.012** (0.004)	-0.016*** (0.002)	-0.028** (0.010)	-0.012*** (0.003)	-0.013*** (0.002)	-0.016*** (0.002)	-0.019*** (0.003)	-0.014*** (0.002)
Construction	0.082** (0.030)	0.034*** (0.008)	0.015*** (0.003)	0.045* (0.020)	0.036*** (0.005)	0.024*** (0.003)	0.020** (0.006)	0.045*** (0.006)	0.019*** (0.003)
Education	-0.020 (0.085)	0.020 (0.024)	0.031** (0.011)	0.014 (0.065)	0.029 (0.015)	0.053* (0.021)	0.023* (0.009)	0.018 (0.017)	0.033*** (0.009)
Health	0.009 (0.007)	-0.002 (0.006)	0.009*** (0.002)	-0.002 (0.013)	0.000 (0.004)	0.003 (0.005)	0.003 (0.002)	-0.006 (0.003)	0.011*** (0.002)
Hospitality	0.081** (0.028)	0.015 (0.011)	0.009 (0.006)	0.056* (0.027)	0.030*** (0.008)	0.017** (0.006)	0.021*** (0.006)	0.032*** (0.009)	0.013** (0.005)
Human Services	0.049 (0.043)	-0.009 (0.014)	-0.045*** (0.005)	0.018 (0.036)	0.046*** (0.010)	-0.104*** (0.025)	-0.022*** (0.005)	0.038*** (0.011)	-0.038*** (0.005)
IT	0.002 (0.019)	-0.095*** (0.029)	-0.033*** (0.009)	0.000 (0.044)	-0.025 (0.013)	-0.027*** (0.007)	-0.043** (0.013)	-0.032** (0.011)	-0.029*** (0.008)
Manufacturing	-0.032* (0.016)	0.004 (0.010)	-0.008** (0.003)	0.009 (0.016)	0.004 (0.004)	-0.002 (0.002)	-0.032*** (0.007)	-0.001 (0.004)	-0.002 (0.003)
Public Services	0.042 (0.026)	0.028* (0.012)	-0.006 (0.003)	0.011 (0.030)	0.014 (0.009)	0.002 (0.004)	-0.003 (0.004)	0.016 (0.009)	-0.004 (0.003)

Transportation	0.037 (0.031)	0.043** (0.013)	0.015*** (0.004)	0.034 (0.029)	0.034*** (0.007)	0.026*** (0.004)	-0.017 (0.013)	0.042*** (0.008)	0.017*** (0.004)
Overall R-Sq	0.054	0.022	0.013	0.026	0.029	0.025	0.026	0.040	0.012
ICC	0.357	0.377	0.406	0.418	0.416	0.423	0.386	0.402	0.404
Observations	652,548	2,754,388	10,161,146	517,286	6,350,362	10,423,718	10,012,012	6,491,213	13,944,517

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note. This table displays the quarterly employment coefficients of IRC attainment from a set of CRE models run separately for each racial, gender, and income group; along with the controls - highest credential attained, demographic controls, HS CTE and non-CTE credits, CTE concentrator, college credits attempted, year-quarter fixed effects, and HS graduation year fixed effects. We clustered the standard errors at the student level.

Table 6: Relationship Between IRC Receipt and Quarterly Log Wages by Demographics

	Asian	Black	Hispanic	Other Races	White	Male	Female	Non-Low-I ncome	Low-Income
<i>Overall IRCs</i>									
Any IRC	0.079* (0.037)	0.035 (0.023)	0.007 (0.010)	0.054 (0.050)	0.109*** (0.014)	0.080*** (0.010)	-0.016 (0.010)	0.040** (0.014)	0.042*** (0.009)
Aligned IRC	0.193*** (0.058)	0.131*** (0.038)	0.149*** (0.016)	0.095 (0.082)	0.173*** (0.024)	0.218*** (0.020)	0.082*** (0.015)	0.104*** (0.023)	0.171*** (0.014)
Misaligned IRC	0.006 (0.047)	-0.011 (0.028)	-0.064*** (0.012)	0.034 (0.061)	0.081*** (0.016)	0.034** (0.012)	-0.082*** (0.013)	0.008 (0.017)	-0.019 (0.010)
IRC Count	0.065** (0.024)	0.024 (0.017)	0.018** (0.007)	0.066* (0.033)	0.054*** (0.009)	0.060*** (0.006)	-0.028*** (0.008)	0.026** (0.009)	0.037*** (0.006)
<i>IRC Clusters</i>									
Agriculture	0.114 (0.111)	-0.004 (0.056)	0.133*** (0.028)	0.023 (0.124)	0.033 (0.030)	0.040 (0.032)	0.108*** (0.023)	0.014 (0.033)	0.102*** (0.023)
Arts	-0.009 (0.121)	-0.250** (0.088)	-0.112** (0.035)	-0.111 (0.151)	-0.072 (0.047)	-0.056 (0.034)	-0.195*** (0.039)	-0.093* (0.044)	-0.118*** (0.032)
BMF	-0.025 (0.063)	-0.080* (0.037)	-0.165*** (0.016)	-0.209* (0.089)	-0.093*** (0.025)	-0.125*** (0.018)	-0.136*** (0.017)	-0.154*** (0.024)	-0.136*** (0.015)
Construction	0.757** (0.267)	0.364*** (0.076)	0.211*** (0.030)	0.501** (0.177)	0.409*** (0.045)	0.297*** (0.025)	0.180** (0.057)	0.502*** (0.053)	0.241*** (0.026)
Education	-0.240 (0.725)	0.232 (0.215)	0.253** (0.098)	0.273 (0.555)	0.231 (0.131)	0.421* (0.188)	0.201* (0.079)	0.122 (0.146)	0.286*** (0.083)
Health	0.081 (0.061)	0.029 (0.051)	0.109*** (0.022)	0.026 (0.110)	0.024 (0.032)	0.018 (0.041)	0.056** (0.018)	-0.044 (0.029)	0.137*** (0.020)
Hospitality	0.679** (0.242)	0.198 (0.101)	0.087 (0.052)	0.579* (0.235)	0.296*** (0.068)	0.157** (0.057)	0.227*** (0.049)	0.314*** (0.074)	0.136** (0.043)
Human Services	0.581 (0.386)	-0.012 (0.127)	-0.334*** (0.048)	0.176 (0.321)	0.499*** (0.094)	-0.910*** (0.224)	-0.121** (0.041)	0.421*** (0.098)	-0.275*** (0.044)
IT	0.086 (0.164)	-0.747** (0.245)	-0.318*** (0.077)	0.046 (0.380)	-0.182 (0.111)	-0.236*** (0.066)	-0.350** (0.117)	-0.219* (0.095)	-0.275*** (0.071)
Manufacturing	-0.236 (0.136)	0.113 (0.086)	0.009 (0.026)	0.157 (0.140)	0.161*** (0.032)	0.070*** (0.021)	-0.267*** (0.058)	0.092* (0.036)	0.084*** (0.023)
Public Services	0.318 (0.223)	0.246* (0.106)	-0.090** (0.029)	0.157 (0.267)	0.186* (0.081)	-0.008 (0.037)	-0.043 (0.036)	0.183* (0.075)	-0.075** (0.028)

Transportation	0.459 (0.283)	0.495*** (0.122)	0.229*** (0.040)	0.487 (0.262)	0.433*** (0.065)	0.341*** (0.034)	-0.118 (0.119)	0.512*** (0.070)	0.247*** (0.037)
Overall R-Sq	0.074	0.033	0.028	0.035	0.043	0.042	0.040	0.058	0.025
ICC	0.384	0.424	0.451	0.460	0.455	0.465	0.430	0.439	0.450
Observations	652,548	2,754,388	10,161,146	517,286	6,350,362	10,423,718	10,012,012	6,491,213	13,944,517

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note. This table displays the quarterly wage coefficients of IRC attainment from a set of CRE models run separately for each racial, gender, and income group; along with the controls - highest credential attained, demographic controls, HS CTE and non-CTE credits, CTE concentrator, college credits attempted, year-quarter fixed effects, and HS graduation year fixed effects. We clustered the standard errors at the student level.